PHD

New product sales forecasting: the relative accuracy of statistical, judgemental and combination forecasts

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TABLE OF CONTENTS

ACKNOWLEDGMENTS 5

ABSTRACT 6

Chapter 1. Introduction 7

1.1. Background 7

1.2. An overview of new product forecasting techniques in current use 10

1.3. Aims of the research 12

1.4. Scope of the thesis 13

1.5. Preview of subsequent Chapters 13

Chapter 2. Quantitative forecasting models 15

2.1. Introduction 15

2.2. The Bass diffusion model 17

2.3. Including marketing covariates in the forecasting model. 20

2.4. Marketing variables in diffusion models 21

2.5. The Bass Diffusion model with marketing variables and a replacement sales covariate 24

2.6. The calibration of diffusion models 26

2.7. A diffusion model with the employment of analogous product sales data 28

2.7. 1. Structured analogies method 29

2.8. Summary and conclusion 31

Chapter 3. Qualitative (judgemental) techniques in new product forecasting 33

3.1. Judgement and new product forecasting 33

3.2. Problems with judgement 33

3.3. Quantitative vs. Qualitative methods 40

3.3.1 Preferences of managers 40

3.3.2 Domain knowledge 40

3.3.3 Availability of the latest information 42

3.3.4 Stability and environmental uncertainty 44

3.4. An overview of judgemental techniques 45

3.5. Selecting experts in judgmental forecasting 54

3.6. Summary and conclusion 56

Chapter 4. Combining Quantitative and Qualitative methods of forecasting 58

4.1. Judgmental adjustment of quantitative forecasts 58
4.2. Judgment as input to model building 60
4.3. Quantitative correction of judgmental forecasts 61
4.4. Combining judgmental and statistical forecasts 63
4.5. Comparing objective and subjective integration methods in terms of producing higher forecasting accuracy 64
4.6 Summary and conclusions 66
Chapter 5. Methodology and Empirical testing 69
5.1. Methodology identification based on ontology and epistemology of the phenomena 69
5.2. Background to the research 73
5.3. Measuring the accuracy of a sales forecasting model 74
5.4. Data sampling and preparing for the analysis 77
5.4.1 Data preparation 77
5.4.2 Fitting the Bass models to the analogous products 79
5.4.3 Using the analogous products to forecast the sales of target products 80
Chapter 6. Applying statistical approaches to the identification of analogies 82
6.1 Benchmarks for accuracy from previous research 82
6.2 Benchmarks for accuracy based on electronic products in the purchased database 83
6.3 Statistical forecasting based on analogies: Method 1 87
6.4 Statistical forecasting based on analogies: Method 2 89
6.5 Statistical forecasting based on analogies: Method 3 90
6.5.1 What makes a good analogy? 90
6.5.2 Use of these characteristics in forecasting 91
6.6 Summary 93
Chapter 7 Using the Delphi method to identify analogies 95
7.1 Implementing the Delphi method 95
7.1.1 Formation of Delphi study several panels 95
7.1.2 The Delphi template outline 96
7.1.3 Ethical issues 100
7.1.4 Testing the template 100
7.1.5 Carrying out the Delphi experiment 100
7.2. Analysis of Delphi survey results 101

7. 3. Combining the Delphi-based forecasts with statistical forecasts 104
7. 4. Summary... 105
Chapter 8 Does using analogies adaptively improve forecast accuracy? **107**
8.1 Formulating the models 107
8.2 Obtaining the models and applying them to the forecasting task 108
8.3. Comparing the statistical and judgmental methods and their integration. 109
8.4 Summary.. 112
Chapter 9 Conclusions and suggestions for further work............................ **114**
9.1 Introduction.. 114
9.2 Main findings 114
9.3 Discussions of the results 116
9.4 Why the specific forecasting task investigated was challenging.............................. 125
9.5 Limitations of the research 128
9.6 Suggestions for further work.. 132
REFERENCES **135**
APPENDICES **157**
Appendix 1. Target products sales data 157
Appendix 2. Analogous products sales data 175

LIST OF FIGURES

Figure 1 Diffusion model... 16
Figure 2 The categories of adopters 18
Figure 3 The products' dates of launch 79
Figure 4 Random selection of analogies 86
Figure 5 Comparing 3 methods... 93
Figure 6 Delphi test questionnaire example... 97
Figure 7 Results obtained by Delphi test involvement 103
Figure 8 All results compare, MdAPEs 111
Figure 9 All results compare, MMAPEs.. 112
Figure 10 All products P-estimates 126
Figure 11 All products Q-estimates 126

LIST OF TABLES

Table 1. Optimum sales trend fit results 84
Table 2. Best analogy results 84
Table 3. Selecting a single analogy or multiple analogies at random results 85
Table 4. All analogies 'p' and 'q' used results 86
Table 5. Using 'p'and 'q' estimates from previous studies results 86
Table 6. Method 1 (using 1 best analogy) results 89
Table 7. Method 2 results (using 3 best analogies).. 89
Table 8. Method 3 results (using more product characteristics) 92
Table 9. Comparing Methods 1, 2 and 3 results 92
Table 10. Delphi survey results.. 101
Table 11. Averages of all analogies available to panel 102
Table 12. Results 'if best analogy was always chosen' 102
Table 13. Compare of the forecasting results... 105
Table 14. Results of using analogies adaptively 109
Table 15. Statistical and judgmental methods, MdAPEs................................... 110
Table 16. Statistical and judgmental methods, MMAPEs 110

LIST OF FORMULAE

Formula 1. Diffusion model with coefficient of imitation................................... 17
Formula 2. Diffusion model with coefficient of innovation 17
Formula 3. Bass diffusion model 18
Formula 4. Sales formula 24
Formula 5. Ordinary Least Squares (OLS) 26
Formula 6. p, q and m in OLS.. 26
Formula 7. Theil's correction model 62
Formula 8. Mean Square Error (MSE).. 75
Formula 9. Mean Average Percentage Error (MAPE)... 75
Formula 10. Actual Percentage Error (APE) 76
Formula 11. OLS fit to annual sales data.. 79
Formula 12. Starting estimates of p, q, and m 80
Formula 13. Average days required to work in order to purchase the product..... 87

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ABSTRACT

This research investigates three approaches to new product sales forecasting: statistical, judgmental and the integration of these two approaches. The aim of the research is to find a simple, easy-to-use, low cost and accurate tool which can be used by managers to forecast the sales of new products. A review of the literature suggested that the Bass diffusion model was an appropriate statistical method for new product sales forecasting. For the judgmental approach, after considering different methods and constraints, such as bias, complexity, lack of accuracy, high cost and time involvement, the Delphi method was identified from the literature as a method, which has the potential to mitigate bias and produces accurate predictions at a low cost in a relatively short time. However, the literature also revealed that neither of the methods: statistical or judgmental, can be guaranteed to give the best forecasts independently, and a combination of them is the often best approach to obtaining the most accurate predictions.

The study aims to compare these three approaches by applying them to actual sales data. To forecast the sales of new products, the Bass diffusion model was fitted to the sales history of similar (analogous) products that had been launched in the past and the resulting model was used to produce forecasts for the new products at the time of their launch. These forecasts were compared with forecasts produced through the Delphi method and also through a combination of statistical and judgmental methods. All results were also compared to the benchmark levels of accuracy, based on previous research and forecasts based on various combinations of the analogous products' historic sales data. Although no statistically significant difference was found in the accuracy of forecasts, produced by the three approaches, the results were more accurate than those obtained using parameters suggested by previous researchers. The limitations of the research are discussed at the end of the thesis, together with suggestions for future research.

Chapter 1. Introduction

1.1. Background

"*New product forecasting is the process that determines a reasonable estimate of sales attainable under a given set of conditions. That is, new product forecasting serves as a reality check by providing visibility to what is likely to happen*" (Kahn, 2006: 7)

The essential first step in the business process for almost every commercial enterprise is obtaining an as accurate as possible sales forecast for its products/services. Invariably, the sales forecast dictates the company's outlook on product range, budget outlays etc.

Forecasting is an important input, if not the most important input, in deciding the company's production parameters price strategy, advertisement spend etc. Hence the need for accurate forecasts is evident. Inaccurate forecasting is sure to damage the company's profitability. Over-forecasting results in inventory costs incurred not only for carrying inventory but also obsolescence costs in a world where the product life cycle continually shrinks. On the other hand under-forecasting leads to the loss of valued customers in increasingly competitive world.

While it may be understood by many that an accurate forecast is needed to have a business advantage, achieving an accurate forecast is not easy in spite of the availability of many forecasting techniques. This problem becomes even more acute if the forecast is for a new product, but the need for accuracy is even more critical as new products are the main means of surviving in a competitive business environment, especially in highly dynamic industries, such as telecommunications or cosmetics (Gooper, 1990; Easingwood, 1986; Narver et al., 2004). It is accepted by many strategists that new products give companies an advantageous position over the competition. Nevertheless, new product introduction has a failure rate in the range 35 - 41% for fully developed products on the US market (Choffray and Lilien, 1986). According to the market research on new product introductions in the retail grocery (Frozen Food Digest, 1997), the failure rate for new product introductions the industry is 70-80 percent. The financial losses due to those failures are tremendous. For example, new product introduction cost for retail grocery stores averages $270 per product, per store (in 1997). And each year, on average every those spends $956,800 (in 1997) to introduce new products that will fail. These numbers point to the need to assess a new product's future potential accurately in order to avoid money losses. In particular, companies need to perform sales forecasting to test whether a strategic concept merits further development and decide whether to launch a new product based on the sales estimates.

When a company develops a new product, it goes through the stages of the strategic planning and concept generation, which includes market revenue assessment. This is followed by the pre-technical evaluation stage, which involves sales potential estimation (forecasting), and then the technical development and commercialisation stages, which are devoted to establishing the unit sales (Kahn, 2006).

In other words, new product development (NPD) involves the direct interaction between strategic management and sales forecasting. In order to implement NPD successfully, managers need to develop a winning strategy as well as perform accurate forecasting, thus they need a powerful forecasting tool, which would allow them to assess the influence of strategic decisions on sales.

However, despite its importance, the relatively small number of studies that have been carried out to date in this area reveal that new product forecasting is a very under researched area. As Kahn (2006: 41) states, "New product forecasting receives considerably less attention, especially when counting the number of publications on each respective topic". This is of particular concern because, as Kahn points out, new product forecasting accuracy on average is tentatively only 50 per cent (though it is unclear which accuracy measure is being used here –a request for clarification from Kahn was not answered). Armstrong (2001) also draws attention to the fact that only a few studies have been performed in new product forecasting and the topic deserves closer attention.

Today, there is a range of statistical tools available to enable managers to carry out forecasting using historic data, and, when sales patterns are relatively stable, more data should lead to more accurate forecasting. However, when it comes to new product forecasting, forecasting becomes more difficult as a company has no available historic data directly relating to the product. While numerous studies have proposed different models to forecast new product sales, there is little systematic understanding about which of these models works best and there is no clear evidence of which of them would be best to recommend for accurate forecasting (Hardie et al., 1998; Armstrong, 2001; Kahn, 2006).

Kahn (2006) categorises new product introductions into the market into several levels according to the extent of the product's 'newness'. According to his findings the greatest accuracy is likely to be achieved, when a new product merely represents a cost improvement on a predecessor (e.g. the new product may be constructed from cheaper materials). In contrast, the lowest level of accuracy is likely to be achieved with forecasts made for a 'new to the world' product, such as the first satellite navigation system that was marketed to motorists. A 'new to the world' product can be defined as one, which satisfies consumer needs by new, innovative means, such as technological innovations, which were not used before for that purpose.

The low levels of accuracy obtained for 'new to the world' products is not surprising as, in the latter case, the company will have no historical sales data, experience or expertise relating to the product, unlike in the cases, where a company has essentially the same product but introduces some innovations related to this product. Absence of product expertise or sales history clearly creates high uncertainty in the estimation of future sales. However, it is important to ask whether low levels of forecast accuracy are inevitable in these circumstances. Could forecast errors be exacerbated by the inadequacy of the forecasting instruments, which are available at present for managers, are current approaches to forecasting inefficient or are there other factors which are unnecessarily contributing to errors? What, if anything, can be done to improve forecasting accuracy? These questions are important and topical for managers, who deal with corporate planning and forecasting, as well as for academics who work in this domain.

1.2. An overview of new product forecasting techniques in current use

Kahn (2006) classified new product forecasting techniques into 3 main categories: Judgemental methods, Customer/Market research and Quantitative methods. Among them he ranked the popularity of the techniques used by companies in new product forecasting and showed that the most favoured method was Customer/market research, followed by Jury of executive opinions (a subcategory of judgmental methods) and Moving Average and other techniques, which fall into the quantitative methods category[*].

Lynn et al. (1999) attempted to establish the most popular forecasting models used by carrying out a survey of 76 industrial new product projects: 38 successes and 38 failures from 38 high-technology and 38 low-technology companies. They found that high technology businesses had clear preferences for qualitative, internal – judgemental forecasting methods, specifically – internal expert judgement and internal brainstorming for identifying successful new products and forecasting their demand. Low technology companies, by contrast, favoured quantitative forecasting techniques, which relied on external data sources received from the results of surveys of buyer intentions and formal surveys through interviews with customers and salespeople.

Fader and Hardie (in Armstrong, 2001) who reviewed existing forecasting models identified the test-market forecasting models, pre-test market models, and judgement- and analogy-based methods as being the most popular models.

The test – market forecasting model represents a case of new product testing in a market setting, so the product marketing plan can be tested in a real situation. The test results are then generalised and sales data are extrapolated for the whole target market to produce estimates of demand.

The pre-test market model is a procedure for collecting primary research data through interviewing target customers or giving them an opportunity to try or purchase the new product (food, cosmetics) in a mock store (a devoted stall in the supermarket etc.) and asking about their intention to purchase or repurchase it in the future. Based on the research results a decision is made whether or not to invest into further new product development. This method is also referred to in the

[*] Those quantitative methods still need some preliminary historic data are available and perform forecasts on the base of them.

marketing domain as the intentions and expectations survey method and will be described later in more detail.

The analogy-based method is a technique, when historic data of analogous products are used to make predictions for the target product. This technique is popular for line -extension products to predict sales of a new product (Kahn, 2006). This approach will also be covered later more extensively.

Fader and Hardie (2005) speculate that simple forecasting models are particularly valuable for forecasting because: 1) managers are normally not highly sophisticated in using statistical instruments, 2) even if managers happen to be such, the upper management often may not be so, thus they would be sceptical of forecasting results, based on overcomplicated methodologies, 3) managers usually have little time for forecasting exercises, so they cannot devote themselves to time consuming forecasting operations.

Overall, it seems that most companies prefer qualitative forecasting methods because of managers' difficulty in understanding, and a general aversion towards, the complex working of quantitative models and a lack of user friendly software (Armstrong, 2001). However, despite the popularity of qualitative methods, these methods have certain drawbacks. Understanding and addressing these could be crucial in companies' battles for competitive advantage. For example, the use of test – market forecasting models carries an opportunity cost for not going to the commercial market earlier as competing companies are very likely to become aware of the new product testing and prepare a responsive strategy to compete successfully. This method also can carry high overall costs. Similarly, the consumer intentions measurement approach is mostly suitable for consumer goods, where samples of products can be given to potential customers, but in the case of high technology high value products, such as new telephones or new telephone services this method seems less sensible because it is difficult to assess the suitability of product features using this method. If the method is used at the concept testing phase before the actual product launch, consumers will be asked about their intentions about buying a product that they are often unable to appreciate. This makes it difficult for them to judge the usefulness or otherwise of the features before they have seen or used the product (Lambin, 2007). Finally, techniques such as Internal Judgement require qualified domain experts, if they are not readily available in the company the wrong expertise will almost certainly result in inaccurate forecasting.

Other researchers (Makridakis and Wrinkler, 1983; Mathews and Diamantopoulos, 1986; Sanders and Ritzman, 2004; Lawrence et al., 2006) have argued that a combination of forecasting methods is most likely to produce better forecasts than either of the methods, quantitative or qualitative, used independently. However, there is a risk that forecasts should not be combined when they are both biased because the combination will reduce the overall forecast accuracy. There exist roughly, four integration methods: i) Judgmental adjustment of quantitative forecasts; ii) Quantitative correction of judgmental forecasts; iii) Combining judgmental and statistical forecasts: a combination of two independently derived forecasts; and iv) the use of Judgment in choosing the inputs to *model building* (e.g., judgment could be used to select the variables for a quantitative forecasting model). However, we could find no studies, which empirically tested the relative effectiveness of the integration methods in the context of new product forecasting.

1.3. Aims of the research

In the light of this background discussion, this thesis aims to contribute to research in this area by addressing the following questions:

1. Is it possible to derive a relatively simple statistical approach to new product sales forecasting that produces forecasts that have an acceptable level of accuracy?
2. What level of accuracy can be obtained by using simple models that allow managers to structure their judgmental inputs into forecasts?
3. Does the integration of statistical forecast and judgment lead to greater accuracy when the demand for new products is being forecast?
4. Which of the three approaches above yields the highest accuracy, under different circumstances?

1.4. Scope of the thesis

The scope of this thesis is defined in terms of the following objectives:

1. To evaluate a number of relatively simple and transparent statistical methods which will allow managers to produce sales forecasts for new products with no previous sales history. These methods will be based on data that is available on potentially analogous products that have been launched prior to the new product. The model also has to allow managers to analyse strategic movements of the company, therefore, it should include external environment variables and reflect their influences on sales dynamics.
2. To evaluate the role which judgment can play in identifying suitable analogies for new product forecasting
3. To find an effective method for integrating statistical and judgmental models, from perspectives of forecasting accuracy and method simplicity.
4. To compare these three approaches in order to find which approach is the most effective/recommendable for managers from perspectives of forecasting accuracy and method simplicity.

1.5. Preview of subsequent Chapters

Chapter 2 reviews the research literature on existing quantitative techniques for new product forecasting. A key perspective in this review is managers' needs for a simple, transparent forecasting tool, which would give a possibility to account for decision making variables, such as marketing mix and external environment impacts.

Chapter 3 considers methods that have been proposed in the literature for performing new product forecasts by means of judgment. As before, these methods have been analysed from the perspectives of accuracy and simplicity.

Chapter 4 explores and compares statistical and judgmental integration methods, which are applicable for new product forecasting. It also considers the reported accuracy and simplicity of these methods.

Chapter 5-7 describes approaches of empirical testing of the chosen methods: statistical, judgmental and their integration in sales forecasting of target products based on analogies. Those forecasting results will be analysed against the benchmarks for accuracy from previous research as well as on benchmarks based on some additional analysis of the products database.

Chapter 8 summarises the research presented in the thesis and considers its limitations. Suggestions for further research which addresses these limitations are also made in this chapter.

Chapter 2. Quantitative forecasting models

2.1. Introduction

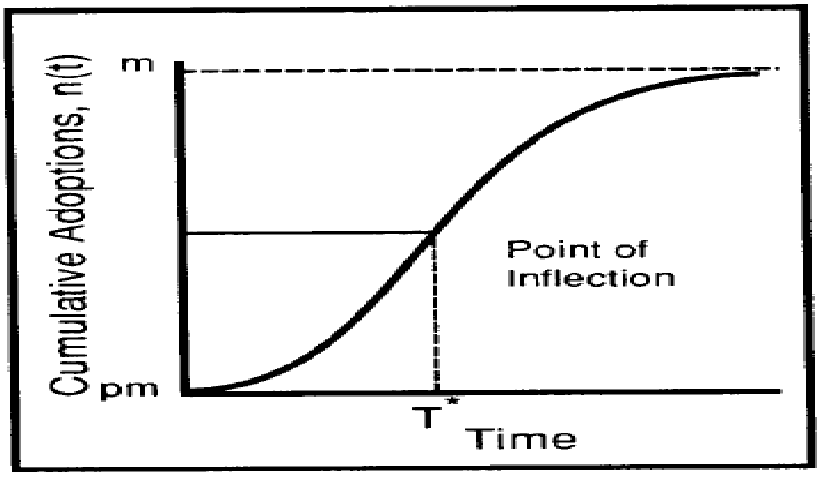
A very large number of methods exist within the quantitative approach for demand forecasting, such as, naïve methods, averaging methods, exponential smoothing methods, regression analysis, time series analysis, and the Box-Jenkins methodology. The most popular techniques among them are regression analysis and time series models (Armstrong, 2001).

Regression analysis seeks to establish a relationship between sales and independent variables, which can give a deeper understanding of the sales figures by explaining variations in sales. However, regression analysis requires a large amount of data for accurate forecasting. Mentzer and Gomes (1989) suggest that a minimum of 20 periods of data is required for regression analysis. In addition, data needs to be gathered relating to the independent variables.

Time series methods help to analyse past patterns of growth and change that can be used to predict future patterns. Because they are limited in their ability to provide explanations for variations in sales historically these methods have tended to be neglected by the marketing literature (Mentzer and Gomes, 1989). However, marketing analysts started to pay more attention to time series models after new user friendly software packages had been produced (Dekimpe and Franses, 2006). Time series models still can be a good tool for assessing both the immediate and long – run performance impacts of marketing activity, such as price, advertisement and promotion.

Particular types of time series model which are widely used in new product forecasting are growth curves (or diffusion models). These curves have been carefully examined by academics since the early 1960s, reflecting the fact that many new product adoptions follow an S-curve when the number of adoptions is plotted against time (see Figure 1).

Figure 1 Diffusion model



Source: Mahajan et al., 1990

There are numerous mathematical ways of representing the cumulative S-shape of the diffusion models. Some of these models are: (i) the pioneering work of Fort and Woodlock (1960) and Mansfield (1961) on the modified exponential, (ii) the Simple logistic model and the Gompertz curve proposed by Gregg et al. (1964), (iii) the Cumulative lognormal curve (Rogers, 1983), the Cumulative lognormal (Bain, 1963), (iv) the Bass model (Bass, 1969), (v) the Extended logistic model (Meade and Islam, 1998), (vi) the Log-logistic model (Tanner, 1978), (vii) the Non-symmetric responding (NSR) logistic model (Easingwood et al, 1981), (viii) the flexible logistic models (FLOG) (Bewley and Feibibg, 1988), (ix) the Inverse Power Transform (IPT), (x) Exponential logistic model (ELOG), (xi) the Box and Cox model, (xii) the Local logistic (Meade, 1985), and (xiii) the Auto-regressive error term model (Man – Molinero, 1980).

There is also a plethora of studies that have been carried out in the application of diffusion models specifically to the NPD (Urban and Hauser, 1980; Wind, 1982; Norton and Bass, 1987; Geroski, 2000). Among all the above models, the Bass model (Bass 1969) became the most popular model for a new product diffusion forecasting due to its simplicity, accuracy and ability to take account of endogenous and exogenous variables.

2.2. The Bass diffusion model

Mahajan et al. (1995: 38) defined the diffusion effect as "*the cumulative increasing degree of influence on an individual to adopt or reject an innovation*". Diffusion models belong to time series approaches, and these models typically predict sales by fitting it an "S" shape curve model, which implies that new product sales initially grow slowly, then the growth speeds up and finally slows down as the market potential is approached (Kahn, 2006). Diffusion theory generally deals with the pattern of new product adoption that takes place in a social community and has been widely used to describe innovation diffusion with applications in high technology (durable consumer products, agricultural, pharmaceutical), as well low technology industries (fast moving consumer goods (FMCG), retailing).

This model describes a "single purchase" consumer's behaviour and was not originally intended to produce forecasts of multiple unit purchases that are made simultaneously or repeat purchasing in later periods.

In 1961 Mansfield developed the internal – influence model (Venkatraman et al., 1994), which purports that diffusion is driven by imitative behaviour within the social system. This model is represented by Formula 1

Formula 1. Diffusion model with coefficient of imitation

$\frac{dY(t)}{dt} = qY(t)(m - Y(t))$, where: Y(t) = the cumulative number of adopters at period t, q is the coefficient of internal influence and m is the potential maximum number of adopters or market potential..

Coleman et al. (1966) proposed an External – influence model, which describes the diffusion process as being dependant on external sources of information of social systems, such as advertising. This model is represented by Formula 2

Formula 2. Diffusion model with coefficient of innovation

$\frac{dN(t)}{dt} = p(m - N(t))$, where p is the coefficient of external influence .

In 1969 Frank Bass introduced a diffusion model, which pulled together the ideas from these earlier models. The basic Bass model is based on two components: the mass media effect, called the coefficient of innovation, or external influence (p), and the word of mouth effect, called the coefficient of imitation, or coefficient of internal influence (q). Mathematically, this model is represented by Formula 3.

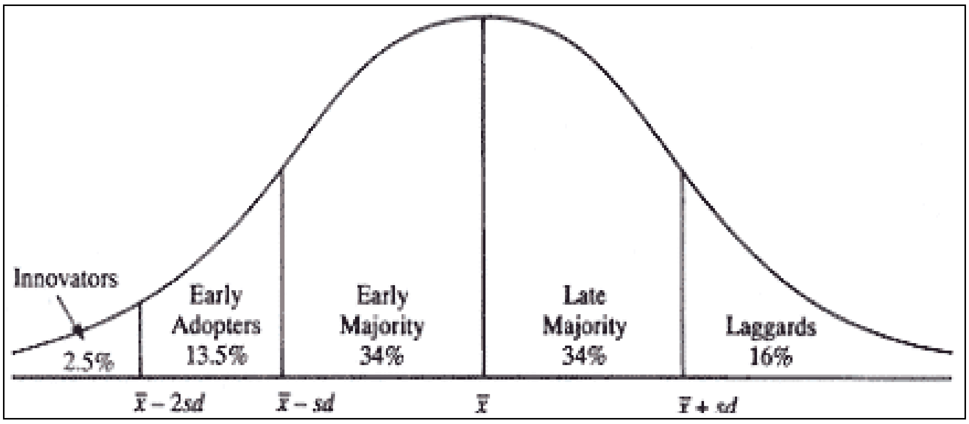
Formula 3. Bass diffusion model

$$Y_t = Y_{t-1} + p(m - Y_{t-1}) + q\frac{Y_{t-1}}{m}(m - Y_{t-1}),$$

where p is the coefficient of innovation, q is the coefficient of imitation and m is the market potential, Y_{t-1} is the cumulative number of adopters up to period t -1.

In 1983 Rogers proposed a method for categorising new product adopters. He suggested that the noncumulative adoption process follows a normal distribution shape and the categories of adopters are divided into Innovators (2.5%), Early adopters (13.5%), Early majority (34 %), Late majority (34 %), Laggards (16%). The Figure 2 below shows these categories of adapters in cumulative and simple adoption graphs

Figure 2 The categories of adopters



Source: Stephenson (2003)

This categorisation approach, as well as the normality of the distribution of simple (noncumulative) adoptions, was questioned by Mahajan et al. (1990). They suggested to describe the adoption process by the Bass diffusion model, where the categorisation of adopters depend on the ‘p+q’ and ‘q/p’ ratio magnitudes, where ‘p’ is defined as a coefficient of innovation and ‘q’ as a coefficient of imitation. ‘p’ represents adoptions by persons, who are not influenced by the number of previous adopters; while, ‘q’ represents adoptions by persons, who are influenced by the number of previous adopters. This model changed the percentage of adopters in different categories into Innovators (0.2 – 2.8%), Early adopters (9.5 – 20.0 %), Early majority (29.1 to 32.1 %), Late majority (29.1 to 32.1 %) and Laggards (21.4 to 23.5 %).

The Bass diffusion model is widely used in the marketing area (Bemmaor, 1994; Dekimpe et al., 2000a; Van den Bulte and Stremersch, 2004) and is highly popular specifically for estimating new product adoptions due to certain strengths, such as:

1) The model does allows the influence of external environment factors, such as marketing and macroeconomics to be included in a parsimonious way. When marketing decision variables follow common patterns, such as an exponentially falling price of the product along the time frame, the product adoption pattern follows, or can be approximated by the Bass model curve (Mahajan et al., 2000).

2) A quadratic function of cumulative sales, which the Bass model assumes, is typical of the sales of most new products, hence the model provides as good a fit to new product adoption history as more complex models do (Chandrasekaran and Tellis, 2007). In this sense the parsimoniousness of the model makes it appealing to typical managers

However, the model is certainly not free from limitations either:

1) The model needs data from the product launch up until the product maturity stage to provide meaningful estimates.
2) The model does not include the *direct* influence of external variables, such as marketing budgets or the economic situation. It assumes, however, that the coefficients p and q capture the effect of such external influences.
3) The p and q parameters are static, so the model assumes that the external environment does not change, which is not the case in the real world.

Nevertheless, for this research the positive features of the model outweigh the negative ones and the use of the model is therefore justified in the light of the aims of this project, which were to find a simple model, which will still comprise the effect of external variables and provide accurate forecasts for new products. This model is of therefore of significant importance for managers, who have no sophisticated knowledge of statistical instruments and yet will be able to understand and interpret the model, thereby avoiding the "black box" problem. This model is also important for its ability to make predictions for completely new products with no prior sales history with the use of parameters of analogous products (this will be explored later in detail).

The earlier attempts to include the marketing variables in the model explicitly will be studies next and considered why the model still works well without them.

2.3. Including marketing covariates in the forecasting model.

"*The ultimate success of any brand depends on the willingness of consumers, once having tried it, to continue purchasing it. In oversimplified terms, persuading the consumer to try a brand is a function of distribution, advertising, and promotion*." (Parfitt and Collins, 1968: 132).When a company creates a strategic plan to meet its market share and profit objectives, it makes strategic decisions about the marketing mix (Kotler, 2008). Firms, engaged in NPD have been classified by Ansoff (1968) (in Wilson and Gillian, 1997) as 'Reactors', who respond to a problem only after it has occurred, 'Planners', who anticipate the likely problems and 'Entrepreneurs', who consider NPD as a high priority for strategic advantage. Thus, in order to maximise value a company needs to be either a Planner or an Entrepreneur, both of which require significant investments. The company should also be able to anticipate the timing of its investment returns and for that it would need to know (i) the level and speed of first time sales, (ii) the level of replacement sales and (iii) the likelihood and possible levels of repeat sales (Wilson and Gillian, 1997).

In order to achieve high levels and speedy sales, the company would need to successfully compete in the market on criteria such as (i) product packaging excellence (ii) price/value for money (iii) advertisement efficiency and (iv) distribution efficiency. In the case of new product development strategic planning, managers face the crucial question of whether 'to launch or not to launch the product' and to answer this they need to estimate future sales in relation to the investments that the project requires, organisational capabilities and market opportunities. Earlier academic studies suggested that a new product launch success depends on the development activities, which need to be done well, independent of the level of innovation of the product mentioned earlier (i.e. product improvement, product line extension, new product to the world and others) (Song and Montoya-Weiss, 1998). Iansiti and Khanna (1995) researched the IBM success history and concluded that the company success depended on not only the product's architectural innovations but also on the company's performance and capabilities in managing the marketing mix variables. Therefore, success of a new product can not be stipulated solely by the innovativeness of the product, but also the management of product introduction plays a significant part in the success. This means, as other studies shown, considering and/or managing internal and external variables, such as price, advertisement, distribution, consumer income is crucial. For example, Radas (2005) established that when breaking the sales down into monthly fractions it can be shown how marketing efforts influence the sales trend significantly. Bayus (1988) examined the impact of marketing mix variables, such as price and advertising on the acceleration of replacement of durable products and found out that price had a large effect on the timing of early replacement, advancing the time by over one year for a 10% decrease in price. Advertising had less impact on the advancing the replacement purchase. For example for a 50% increase in advertising the replacement timeframe is brought forward by around 11 months.

Thus, it is reasonable to suggest that the incorporation of marketing mix information into the sales forecasting model will give higher forecasting accuracy. Attempts to incorporate marketing mix variables explicitly into the diffusion models have been made by several researchers. Some of these models, which have incorporated price and advertising variables, are discussed below.

2.4. Marketing variables in diffusion models

The Bass model went through refinement in order to make it more sophisticated in terms of including external variables, so that it had an improved response to environmental heterogeneity. Robinson and Lakhani (1975) performed pioneering work, trying to include marketing variables explicitly in the diffusion model. They combined the ‘learning curve’ phenomenon expressed in a mathematical formula and the Bass diffusion model to represent a dynamic model of the market in terms of the sales volume. The market size in the formula suggests the number of potential buyers, who are likely to make a first purchase.

Their formula is intended to define a pricing strategy for successful business evolution. However, they did not provide any empirical evidence of the formula’s validity, and later empirical tests performed by other researchers revealed the formula’s deficiencies. For example, the formula, assumed that advertising has an identical effect on innovators’ and imitators’ behaviour, but Simon and Sebastian's (1987) rejected this hypothesis, doubting its practical validity. Indeed, in a general sense, advertising is supposed to influence innovators, while imitators tend to follow innovators due to the word-of-mouth effect. The poor performance of its model was also discovered by Horsky (1990), when he carried out a research with the data on the use of durable products.

Later, other researchers developed improved models, which gave better forecasting accuracy by incorporating specific marketing variables in the models. Horsky and Simon (1983) examined the effect of advertising on sales of new infrequently purchased products. Their formula is analogous to the Bass diffusion model, however it includes advertising expenditure in the model. They reconsidered the coefficient of innovation (p) as a parameter dependent on the external variables (such as advertisement, price, economic and demographic variables) and presented it as a function of advertising: $\alpha + \beta \ln A(T)$ (where $A(T)$ is the advertising function of T = time period). While all previous studies which incorporated marketing variables in the diffusion models assumed that the coefficient of innovation was defined by the product ‘innovativeness’ only and added functions of advertising or price in addition to the innovation and imitation coefficients, Horsky and Simon (1983) determined the coefficient of innovation as a dependent function of advertising and included the coefficients of effectiveness of information sources. This approach gives managers a possibility of measuring the effect of the advertisement campaign on sales, although it has to be noted that the accuracy of the forecast would depend on how effectively these campaigns are planned and executed. However researchers did not find a generic magnitude of advertisement elasticity (Parsons, 1975; Assmus et al. (1984); Simon and

Sebastian, 1987; Sethuraman and Tellis, 1991), but reported various values for different products and markets, which is logical from a practical perspective.

Later, Simon and Sebastian (1987) carried out research measuring the impact of advertising on diffusion of new telephones in West Germany. They suggested that advertising can have an effect on both the innovation and imitation coefficients, and developed a formula based on the Bass diffusion model, by adding an advertisement expenditure function. Their empirical results revealed slightly better predictive validity of the 'imitation model' than that of the 'innovation model'. By this they rejected the hypothesis made earlier by Robinson and Lakhani (1975) that advertising has an identical effect on the innovation and imitation coefficients. They (Simon and Sebastian, 1987) suggested the advertising strategies (e.g. message composing, budgeting, and use of the channels of communication) targeted at innovators and imitators should be different. To support this suggestion they tested both the 'imitation model' and the 'innovation model' (proposed earlier by Horsky and Simon (1983)) separately which included the advertisement campaign function explicitly and found that the 'imitation model' yielded results which fitted the data better.

Horsky (1990) is one of the few researchers, who has included several exogenous variables, such as wage levels, prices, size of the population and income into diffusion models and suggested that they influence the market potential. He tested eight models: the simple Bass diffusion model and its special cases such as the Dynamic Bass model which takes into account population growth, the Income price model, the Income – price with enhanced utility model, the Income-price and information (the coefficient of innovation) model, the Income – price with the word-of-mouth information model, and the Income – price with enhanced utility and word of mouth information (the coefficients of innovation and imitation) model. He used adoption data for TVs and dishwashers, dryers and other durables in the UK. The empirical results showed that the simple Bass model did not work very well in all cases, whereas the models, which incorporated marketing mix variables, showed better results.

The above studies demonstrate practical validity of incorporating marketing variables into forecasting models, revealing that sophisticated models improved forecasting accuracy although it certainly demands bigger investments of time, effort and money.

2.5. The Bass Diffusion model with marketing variables and a replacement sales covariate

Throughout the earlier discussion it was stressed that sales forecasting is important, however, diffusion models are used for product adoption behaviour, which means first purchases only. However, replacement sales represent about 70% of total sales (Horsky, 1990), and in order to obtain a complete sales forecasting formula, a sales replacement covariate needs to be included in the model.

Olson and Choi (as cited in Islam and Meade, 2000) incorporated a replacement covariate in the diffusion model as an additional factor. They described the complete function of sales as below:

Formula 4. Sales formula

$$S_t = x_t + R_t + \varepsilon_t$$

Where,

x_t - the sales in period t due to first time purchases,

R_t - the replacement sales

ε_t - noise

Islam and Meade (2000) described various replacement models represented by probability distributions of the time between successive purchases. These included the triangular, Poisson, Gamma, Rayleigh, Weibull and the truncated normal distributions which have been suggested earlier by other researchers. Among these models, the ones based on the triangular distribution and Poisson distribution were defined as simple models. They also tested these models for forecasting accuracy and reached the following conclusions: (i) the naïve replacement models such as Triangular and Poisson performed moderately well in most circumstances with Poisson showing the highest frequency of successful predictions, (ii) the Rayleigh was the poorest performing model, (iii) the Gamma outperformed the Rayleigh, (however the model parameters estimations failed in 60% of occasions), (iv) the truncated normal model had a performance similar to the Gamma.

There are several studies, which have developed models incorporating both sales replacement covariates *and* marketing mix variables explicitly in the Bass diffusion model. (e.g. Robinson and Lakhani, 1975; Horsky and Simon, 1983; Simon and Sebastian, 1987; Horsky, 1990; Mesak and Berg, 1995). Mesak and Berg (1995) suggested that price may influence the market potential, the coefficient of imitation and the coefficient of innovation. They also investigated the dependability of replacement purchases on price, assuming that price affects the timing of replacement purchases. The empirical results of their work revealed that if first purchases are price sensitive, replacement purchases may or may not be price sensitive, but if replacement purchases are price sensitive, first purchases are always so. They also discovered that first purchases of price sensitive durables are best predicted by the mixed influence model which takes into account external and internal influence. They also found that the best forecasting model for price insensitive durables adoption was the internal influence model ('the imitation model'). However this finding is in contrast to the results of earlier research performed by Horsky (1990) as he found the external information model ('the innovation model') has better predictive power for price insensitive durables. It is reasonable to suggest, though, that such price insensitive durables, like TVs and refrigerators are unlikely to be bought solely due to the word-of-mouth effect as suggested by Mesak and Berg (1995). It is more likely that the external information, such as advertising, will have a powerful effect on consumer's minds to make a purchase as suggested by Horsky (1990).

Therefore, the Bass model with the marketing covariates as well as replacement incorporation proved further the feasibility of including external variables into the forecasting model. However, those diffusion models with explicit inclusion of external variables are obviously complex to understand, require significant efforts and time to collect all the necessary data, there is still a simpler way of including external variables. Thus, Bass et al. (1994) also tried to refine his initial diffusion model and incorporate marketing mix variables but in a simpler way. To achieve this, they developed a generalised Bass model (GBM), which embraces marketing efforts dynamics. They explored how decision variables affect the Bass model in terms of increase of forecasting accuracy. They utilised such marketing mix variables as price and advertising and compared the forecasting results, based on empirical data with the forecasting by means of General Bass model. In fact, they demonstrated in their research that the Bass diffusion model works perfectly without the marketing covariates included explicitly because those covariates are already implicitly included in the ‘p’ and ‘q’ coefficients. They also stressed that GBM works perfectly, as long as the marketing efforts are constant or change at a constant rate.

Therefore, the Bass diffusion model appears to be the model, which balances simplicity, with accuracy and an ability to take into account external variables and is widely known as an accurate forecasting tool.

2.6. The calibration of diffusion models

In order to apply a diffusion model to new product forecasting, the model parameters need to be determined. Attempts have been made to estimate these parameters using a number of approaches. Ordinary Least Squares (OLS), was proposed by Bass (1969) and gave a good fit to the sales curve. This method can be applied by fitting the following regression model to the data (e.g. see Franses 2009):

Formula 5. Ordinary Least Squares (OLS)

$$S_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-1}^2$$

Where S_t = the number of adopters for year t

Y_{t-1} = Cumulative number of adopters for all years up to year t-1

and the bi are the parameters of the model

It can be shown that estimates of p, q and m can be obtained by solving the following equations:

Formula 6. p, q and m in OLS

$$b_0 = pm$$

$$b_1 = q - p$$

$$b_2 = q/m$$

However OLS was found to give a poorer fitting model when ‘best fit’ is defined in terms of mean absolute deviation and mean squared error than models derived through Maximum Likelihood Estimation (MLE) and Non – Linear Least Square Estimation (NLLS) (Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986). Schmittlein and Mahajan (1982: 62) also stated that the MLE approach allows the recommended sample size to be determined for a given level of forecasting accuracy and also allow calculation of approximate standard errors for the decision parameters p, q and m. They reached their conclusion based on Rao’s (1965:56) statement that “maximum likelihood estimates are best asymptotically normal, consistent and asymptotically efficient”. However, the ability of the model to calculate an approximate standard error has been questioned by Srinivasan and Mason (1986), saying that the MLE considers only sampling error, but seriously underestimated the standard errors of p, q, and m. They proposed as an alterative a Nonlinear Least Squares (NLS) estimation of the decision parameters, which takes into account total error and so gives valid results. Van den Bulte and Lilien (1997), noticed, however, that NLS is biased on determination of the decision coefficients and they identified how these biases are associated with the number of observations. A small number of observations can lead to significant biases in the estimates. For example it is not untypical to have a 20% underestimation of market potential (m) and the coefficient of innovation (p) , and a 30% overestimation of the coefficient of imitation (q).

While there is no general explicit preference for either MLE or NLS to be used for calculating the diffusion model parameters (Radas, 2005), both of the methods have significant shortcomings from the perspective of practising managers. First, the models require starting values for p, q and m. This requires using either valid expert knowledge to estimate those values, or prior market data available to find the starting values, by the means, of say, Ordinary Least Squares (OLS). This potentially leads to these problems: a) a wrongly selected starting values can give a non – valid final result, b) additional time and financial and physical resources are required to perform accurate forecasting. Second, while both of the methods, MLE and NLS are understandable to professional statisticians, they are likely to create a problem of 'black – box' syndrome for managers, who may therefore be sceptical of the forecasts produced by the methods.

Other researchers have tried to find generalised values for 'p' and 'q'. For example, Lawrence and Lawton (in Wind et al., 1981) found empirical evidence that the value of 'p+q' lies between 0.3 and 0.7. Mahajan et al. (1990) found that q/p ratio ranges from 9.0 to 85.7 for different industries. Sultan et al. (1990) performed meta – analysis with the use of data across 213 applications and suggested average values for the coefficient of innovation as 0.03, in the range of values 0.000021-0.03297 and for the coefficient of imitation the value as 0.38, in the range of 0.2013-1.6726. Lilien et al (1999) reported the mean values for p and q as 0.047 and 0.289 respectively and for cellular telephones 0.008 and 0.421 are the specific values.

Another possible way for defining these parameters is to find analogous products which are likely to have similar parameters and then use these ready coefficients instead of going through a complex process of calculations.

2.7. A diffusion model with the employment of analogous product sales data

As was explained earlier, the success of a new product depends highly on the company's planning and execution process. As a part of the planning, sales forecasts needs to be worked out in order to estimate future prospects of sales. This means that the managers will need to perform forecasting without having any historic sales data available. Other than using published mean industry values for p and q, the only way to apply diffusion models in this case is to use the sales history of analogous products, which have been launched earlier. The approach is widely used in practice, but researchers stress that choosing analogous products correctly requires a meticulous and structured approach, otherwise there is a high risk that sales forecasts will diverge significantly from the actual data.

2.7. 1. Structured analogies method

Analogies "contain information about similar situations in the past" (Green and Armstrong, 2007). The outcomes of similar situations from the past may help a marketer to forecast the outcome of the new situation. On this rationale, analogies of the sales of similar products introduced in past can be used for the sales forecasting of new products. Green and Armstrong (2007) noticed that people often use analogies to make forecasts, but they do not do so in a structured manner. For example, they might search for an analogy that suits their prior beliefs or they might stop searching when they identify one analogy. In general, structured analogies were found to be more accurate than unaided judgement in forecasting the outcomes of conflicts in Green and Armstrong's study (46% conflicts were correctly forecast against 32% in the case of unaided judgement). The question, then arises, what is meant by similarity?

Thomas (1985) stressed that identifying similar products is a difficult task because they can be similar in some aspects, but not in others. He proposed an evaluation process, which helps to identify similarities and rate the degree of similarity. He suggested that the evaluation needs to be made on the basis of:

(i) environmental factors relating to the product, such as: economic, technological, political, regulatory, ecological and social factors.

(ii) market structure: including market potential, likely sales history, barriers to entry, number of generic competitors, type of generic competitors and segmentation,

(iii) buyer behaviour: including the buying situation, the purchasing decision process, choice attributes, and buying centre;

(iv) the marketing strategy associated with the product, such as its price, the way it is promoted and the method of distribution

(v) characteristics of the innovation, such as its relative advantage, its compatibility with existing products, its complexity and divisibility and the extent to which its innovations can be communicated to potential purchasers..

The similarities are rated and an overall score calculated among the candidate products or services. Thomas (1985) carried out forecasting using analogous parameters in a diffusion model and attained sales forecast that were on average about 25% higher than the actual data, but with a very similar growth rate. The author accepts that it is an even more difficult task to obtain all the necessary information for identifying similarities and it costs time and effort. However, this approach would have potential value for managers with little experience or for forecasting in international markets.

There are other studies, where similar methods for structuring analogies methods have been successfully used to improve forecasts. For example, Lee at al., (2007), used analogous data of similar special events, namely product promotions, in order to make estimations of the effects on sales of forthcoming promotions. They identified similar products by creating a database of multiple cases, and used a computer tool to automatically highlight similar events, rank them in terms of their similarities and then estimate the effect of any differences between the analogy and target promotions. They found that this approach significantly enhanced forecasting accuracy. They also found that it is important for all of those stages to be carried out because going through just first two stages i.e. data base creation and finding similarities did not give any advantage in forecasting accuracy.

Ilonen et al. (2006) also attempted to find a more practical and automatic analogy-based forecasting tool for analysts. They used a self-organising map (SOM), developed by Kohonen (1990) for finding suitable analogous products according to the economic, technological and social market characteristics in several countries. These analogous data were used in forecasting ICT (information and communications technology) innovations by means of the Bass diffusion model. The SOM software helped to automate the search for similar counties according to country characteristics. The system automatically selected analogous products in a similar country and searched for the best data fit by means of the Bass diffusion model. The approach had a potential problem that product diffusion could depend only on some of the specific country characteristics, so innovation diffusion even in a similar country would follow a different pattern. In order to minimise risk and also to examine the Bass model bias, they deliberately added the product specific diffusion values to the country data in the SOM and labelled it as SOM2 where the original model is named as SOM1. Not surprisingly, SOM2 improved forecasting accuracy, but in general, as they summarised, the difference between the forecasting results obtained by the models (SOM1 and SOM2) were “not dramatic”. The model seems to be an effective and a user friendly tool, which would help corporate analysts to have access to automate forecasting process without having forecasting expertise. However, the authors recognised that the model versatility is questionable, since the country effects do not necessarily give similar diffusion results, for example, the consumer loyalty towards products in a certain price range does not necessarily depend purely on consumer’s wealth, but may also depend on other factors such us habits, traditions and values. Therefore, it is most likely that managers would still need to insert product specific diffusion values to the model, in order to receive valid results in real situations.

In summary, as recent research demonstrates, this technique of using structured analogies has potentially high value for managers, who lack previous experience and expertise. It gives them the possibility of avoiding having to make judgements that require high domain knowledge and instead it provides a systematic procedural tool with incorporated knowledge.

2.8. Summary and conclusion

There is a plethora of statistical tools, for performing sales forecasting, among them, the Bass model became the most popular model for forecasting new product diffusion due to its simplicity, accuracy and ability to take account of endogenous and exogenous variables. The importance of incorporating marketing variables into a forecasting model has also been widely discussed by academics. The Bass coefficients, ‘p’ and ‘q’, reflect the influences of advertisements and “word of mouth” on the product adoption process. Some academics (Horsky and

Simon, 1983) have gone even further and estimated the coefficient of innovation ‘p’ to be defined by price, economic, demographic and other external variables.

While one study (Song and Montoya-Weiss, 1998) suggested that the inclusion of marketing variables does not increase forecasting accuracy of product diffusion, others (Radas, 2005; Iansiti and Khanna, 1995) have found that for sales forecasting rather than product diffusion, and for smaller time periods (months instead of years), marketing variables play a significant role in determining a sales curve’s shape and lead to statistically significant improvement in the model’s forecasting ability. Bass came to a perfect way of explaining how the Bass diffusion model allows incorporating those external variables in a simpler way, by developing a General Bass Model.

Interestingly, none of the studies involving marketing variables were carried out for new product forecasting based on the analysis of analogous products’ sales histories. Given the success of structured analogies methods in other areas of forecasting the further exploration of a structured analogies approach in new product forecasting seems worth pursuing. This would involve finding the best analogies by taking into account the products’ features and external environment conditions.

Chapter 3. Qualitative (judgemental) techniques in new product forecasting

3.1. Judgement and new product forecasting

As elaborated in the previous chapter, quantitative methods provide one option for forecasting new products sales. Among the quantitative methods, using historic sales data of analogous products (Thomas, 1985; Jun et al., 2000) appears to have substantial potential for getting an accurate forecast for new product sales. However this approach may not work in unstable environmental conditions and competitor's reactions, special events and influences of other external factors cannot be structurally included in the approach and hence forecasting accuracy could not be guaranteed. In such cases, when environmental changes (internal and external) need to be considered, a judgemental approach is potentially useful. However, there are many factors, which need to be taken into account when making judgemental forecasts in order to obtain improved results, such as the potential bias of experts, judgement reliability, the degree to which information used by the judges is up-to-date, the ability of experts to use the information adequately, the judgemental methodology's inherent capability as well as limitations in making accurate predictions and the expertise of the forecaster.

3.2. Problems with judgement

"Inconsistency and bias are the two primary negative influences affecting expert opinion" (Armstrong, 2001: 60). "In general, people are not consistent. Imperfect reliability is observed in nearly all human behaviour." (Armstrong, 2001: 81). Inconsistency is manifested when a person makes different judgements when given exactly the same information at different points in time. Error in forecasting is partly a product of such inconsistency and hence inconsistency is one of the most important concerns that needs to be accounted for when forecasting. Judgemental consistency is well known to decrease as the environmental uncertainty increases. Also, an increase in the volume of information, human memory limitations and the limited information processing capacity of humans all contribute to judgemental inconsistency. Another view is that inconsistency could be the result of reliance on perception and intuition instead of analysis. Yet another opinion is given by Stewart (in Armstrong 2001) who outlined that certain factors such as stress, time pressure, forecasters' confidence levels and difficulties in acquiring information can all have an impact on judgemental consistency.

In addition to inconsistency in judgements, judgemental forecasts are often biased -in that they systematically over or underestimate outcomes. Some laboratory studies have suggested that judgement is superior to statistical models once bias has been eliminated (Ashton, 1985), though this is highly difficult to do in practice. There are a number of well documented judgemental biases.

Tyebjee (1987) highlighted main three sources of bias in a new product forecasting:

(i) *the post decision audit bias*, which arises from the fact that only products which forecasted to be successful are launched in the market;

(ii) *the advocacy bias*, is the bias when product developers want to advocate their product by overestimating its future demand and prospects; and

(iii) *the optimism bias*, when managers, who worked on the project also make emotional commitments towards it and start looking at things in an optimistically biased way. The project participants are prone to concentrate selectively on information, which supports their optimistic bias. In this case, neutral, external participants are recommended to take parts in forecasting process, because they do not share same optimism with the project stakeholders (Heath and Gonzales, 1995; Kahneman and Lovallo, 1993).

Eroglu and Croxton (2010) tried to investigate deeper reasons behind sources of bias and to scrutinise the forecasters' individual characteristics, such as personalities, their motivation, orientation and locus of control. Their findings revealed that personality significantly influenced forecast biases. The judgmental adjustments of statistical forecasts suffered from anchoring and overreaction biases if an introvert personality is involved in the forecasting (i.e. introverted forecasters tended to place too great a weight on the latest sales figure –anchoring is explained in more detail later), while the forecasts of extraverts had less anchoring and overreaction biases. They also found that locus of control significantly influenced how the judgments were performed. The employees, who believed that their actions would have minimal effect on forecasting outcomes, were reluctant to make any significant judgmental adjustments to forecasts. The motivation orientation had a significant effect on forecasting biases but none of the motivational orientation subscales affected forecasts in the wrong (opposite) direction. Overall, these findings suggest that personalities do have a very significant impact on forecast biases.

Kahneman and Tversky (1979, in Hogarth and Makridakis, 1981) defined more sources of bias which apply generally to human judgment under uncertainty. These include:

(i) **Availability Bias**: this occurs when forecasters judge the probability of future events based on the “availability” (e.g. the ease of recall) of similar events in their memory. Human memory is organised so that events which are most readily recalled are likely to be those that were most recently heard, or those that are most salient, such as information widely broadcast in the media. For example, a forecaster may easily recall a recent new product launch which generated low sales and this may significantly influence his or her perception of the chances of a forthcoming product achieving a profitable level of sales.

(ii) **Selective perception bias**: people tend to structure problems based on their own perception and experience. For example, the same problem can be perceived by financial managers, from a financial point of view, by technical managers, from a technical point of view etc., so that information, which is inconsistent with one’s own views tends to be omitted.

(iii) **Frequency Bias**: when judging the strength of predictive relationships people tend to use the actual frequency rather than the relative frequency. For example, poster advertising campaigns may have been associated with 10 successful product introductions while radio advertising was associated with only 5 successes. Thus poster advertising is regarded as being more effective, ignoring the fact that it has been used in 30 product introductions, yielding a relative success rate of only 33% while radio advertising has only been used in 10 introductions and hence has a success rate of 50%

(iv) **Anchoring and adjustment bias**: whereby people make estimates by starting with an initial value (the anchor) and adjust that value to arrive at the forecast. This adjustment has a tendency to be too small (i.e., the anchor has undue influence on the estimate). Harvey and Harries (2004) also refer to "mental anchoring" wherein experts rely mostly on their previous forecasts and make some adjustments, anchoring to the original prediction as a baseline. This may result in underestimation of changes, which is also called the "trend damping effect" (Harvey and Bolger, 1996)

(v) **Conservatism Bias**: Similar to anchoring bias, this bias is failure to revise judgements sufficiently in the light of new information. People are prone to give heavier weighting to their own judgement and are reluctant to change it even in the light of new information. Conservatism also may mean that experts put more weight to someone's opinion, which matches their own rather than spending time to consider other alternative opinions (Harvey and Harries, 2004). For example, in the case described by Fintzen and Stekler (1999), the 1990 recession in the US was not predicted because the majority of experts failed to foresee the likelihood of a recession, even though a number of forecasters did correctly forecast it. It appears that the voice of the minority was not paid due attention.

(vi) **Bias resulting from habit**: This bias arises due to people choosing "habitual" alternatives. For example, according to IMF (International Monetary Fund), the global economy has had a very sustainable growth period since the Second World War (Finfacts, 2003) and hence forecasters estimated only a slight decline in the US economy in 2007 with further recovery in 2008. However, in the 2008, the global economy was hit by recession. The "habitual" increasing trend might have had an impact on the estimations.

(vii) **Data presentation bias**. Human opinion can be influenced by the order of data presentation. For example, information presented first can have a larger impact than information which is subsequently presented. The phenomenon is called 'primacy'. In contrast, in other circumstances the most recently presented information –and hence the information which is presented last -could have a bigger impact, which is known as ‘recency’ bias. Another possibility of bias resulting from presentation format can result from the high conviction power of logically presented data which has the effect of causing people to omit critical reasoning. When an argument is logically structured and supported by consistent examples, people may fail to notice slight signals, which undermine the argument and fail to question it. Harvey and Bolger (1996) explored the effect of the presentation format of the data (i.e. tabular form and graphical form) on judgmental forecasting accuracy. They found that in the case of trended data series, the “trend damping effect” (as in the case of anchoring and adjustment Bias) is likely to occur if the data are presented in tabular form. However, if the data does not have a trend, presenting it in tabular form does not appear to be detrimental to forecasting accuracy.

viii) Representativeness Bias: This is the situation where a person, object or process is judged to be belonging to a particular group. This judgment is arrived by making an assessment of how representative the person, object or process is of the group. This may typically involve “stereotyping”. For example, if someone considers a pattern in a sales graph as belonging to the category “random pattern” rather than “systematic pattern” they will base their judgement on their stereotypical view of what they think a random pattern is (Goodwin, 2002: 128) and vice-versa. As a result people may wrongly see systematic patterns in what is really random behaviour. On the other hand, by assuming the pattern to be random one can miss the vital underlying feature of the data. This bias may lead to a wrong forecast because all available information is not likely to be considered in the forecast.

(ix) Justifiability: If a decisions is supported with apparently rational arguments, people tend to accept the decision even if it is wrong. Thus, abilities of a forecaster to justify a case may wrongly be confused with expertise to make an accurate forecast.

(x) “Best guess strategy”: This bias comes from simplification by ignoring the uncertainties and relying on the “most likely” scenario. When the uncertainty is high it is very difficult to predict outcomes and people may tend to stick to the “most likely scenario”, based on analogous or stereotypical cases.

(xi) Complexity bias: Too much information places a cognitive burden on human memory and may have a detrimental effect on prediction accuracy. Along with this information overload, time pressure and distractions lead to decrease in consistency of judgement.

(xii) Emotional stress bias: Further to what is mentioned above in the complexity Bias, emotional stress could all have impact on the psychological disposition that will affect the expert's ability to make accurate judgments.

(xiii) Social pressure bias: This is where a majority of people cause the judgements of a minority of people to be distorted. A well known effect discovered by Solomon Asch (Shuttleworth, 2008) can serve as an example for this type of bias. In his experiment, a group of people were shown several lines of different length and were asked to name a longest one. All of the group members except one were instructed in advance to point to a wrong line as the longest one. When all the group members confidently pointed to the wrong line, the member who was not aware of the scheming also pointed to that line, since he either believed the opinion of majority rather than his own common sense or he was under social pressure to conform. Since sales forecasts are often made by groups of people this bias has the potential to have a significant effect on forecast accuracy.

(xiv) Consistency of information sources bias: More information can lead to increased confidence, but not necessarily to increased accuracy. Hence even if the information seems consistent, it may not have a beneficial impact on predictive capability.

(xv) Question format bias: It is well known that how the problem is formatted and presented to people influences their subsequent judgements. For example a question to find if a consumer prefers a low price or additional facilities for a slightly higher price can be structured in different ways, affecting the consumer's answer. The contrast between a) would you prefer a cheaper product with less benefits to more expensive products with additional facilities and b) would you be willing to have important additional facilities for a small increase in price is evident. The keywords, like "cheaper", "prefer", "important", which subconsciously influence people’s attitude towards price and additional facilities. Moreover, the affirmative format of the question encourages an affirmative response.

(xvi) Wishful thinking bias: Preferences for particular outcomes may affect the predictions. Often, when managers develop projects, they “wish” it to be successful, and therefore have a bias towards predicting the preferred outcome.

(xvii) Illusion of control bias: Greater control can be gained over many tasks as a person acquires greater skills and experience and as they apply more effort to the task (Typical examples are driving a car or playing a musical instrument). As forecasting is also perceived to involve skill and effort, people may wrongly infer that they have some control over the outcome of the process they are forecasting. This may lead to overconfidence in the potential accuracy of forecasts and a rejection of information that may suggest that the forecasts are likely to be wrong.

Collectively, these biases suggest that judgemental forecasting needs to be used with great care in order to obtain reliable and accurate forecasts. Unaided judgement is not likely to bring reliable results and therefore different technical approaches have been suggested to be used in order to overcome the drawbacks of judgement (these are considered later in the chapter). The presence of these biases also suggest that it would be reasonable to assume that objective statistical forecasting methods will be superior in accuracy and reliability to judgmental forecasts. However, the opinions of academics and practitioners are often split: while some of them advocate statistical methods others prefer judgemental methods. It seems likely that the relative advantage of the methods is contingent on the circumstances surrounding a particular set of forecasts. In the next section we consider the rationale for preferring one of the methods over the other and the circumstances that may favour each method.

3.3. Quantitative vs. Qualitative methods

3.3.1 Preferences of managers

McCarthy et al. (2006) reviewed the evolution of sales forecasting management over the last 20 years, in relation to the use of forecasting techniques (judgemental and statistical) and satisfaction with their performance in practice. After reviewing the relevant academic studies, they found out that managers still preferred qualitative methods to quantitative methods and among the most favoured were: "Jury of executive opinions", followed by "customer expectations" and then by "decomposition" of sales and "force composite methodologies" (details of these methods are described later in this paper). It shows that managers are still mostly prone to trust executive opinions, rather than statistical methods.

It has been suggested that reasons for managers' preference for judgement over statistical tools are primarily a lack of relevant statistical data and increased environmental uncertainty (Sanders and Manrodt, 2003). Another reason is the desire to have a "sense of ownership", whereby managers try to ensure that they personally take a part in the forecasting process which they regard as important for their decision making (Goodwin, 2002). Also, many companies lack personnel who have the expertise to apply statistical methods.

3.3.2 Domain knowledge

"*Quantitative methods are essentially statistical extrapolations of past trends; the judgemental approach relies more on people's contextual knowledge and intuition*." (Kuhn and Sniezek, 1996: 231). The issue of which forecasting methodology (quantitative or qualitative) is better in terms of accuracy has been much debated (Sanders and Manrodt, 2003). However, a key factor appears to be the domain knowledge of the judgmental forecasters. For example, Armstrong (1983) analysed the accuracy of judgemental and extrapolation methods in forecasting annual earnings and found that judgemental methods gave more accurate results than extrapolation methods. The main reason for this was considered to be the availability of domain and tacit knowledge of experts who used this to make their judgmental forecasts, whereas extrapolation methods cannot take into account this additional information. (However, this conclusion was contested in Armstrong’s later book in 2001 which brought to light more recent research that testified against judgement's reliability and superiority (Armstrong, 2001: 91)).

Song et al. (2007) carried out research, which compared the forecasts of the National Football League games results, performed by 70 experts and 32 statistical models. They also considered if updated information improved judgemental forecasting accuracy. They compared experts’ predictions and predictions made by statistical models against the “Las Vegas betting line” (the terminology they used belonged to games prediction rules) and found no significant statistical difference between judgmental and statistical approaches in predictive validity, however both of them were outperformed by the ‘betting line’. They revealed that variation in successful forecasts made by experts was significantly higher than those obtained by statistical tools.

They suggested that experts might have performed as well as statistical systems because experts with high level of domain and tacit knowledge were involved (some of them are professional footballers in the past others are experts in the field). This contributed to high accuracy in the predictions. The authors also suggested that these experts might have obtained inner information from the teams’ coaches or players, which also might have influenced their judgements. They also could review statistical predictions, therefore could have combined own expertise with other predictions to enhance their own quality of predictions. Hence, in this case the power of judgements is put under doubt. They also concluded that the influence of contextual information did not improve judgemental accuracy considerably, since in the second half of the season the relative accuracy of experts declined in spite of the availability of additional information. However, judgemental methods were found to have achieved better accuracy than the naïve statistical method did, which is consistent with many previous studies (Green and Armstrong, 2006; Kahn, 2006; Lawrence et al., 2000; Webby and O’Connor, 1996). This suggests that more sophisticated statistical tools than naïve extrapolation are needed to achieve accurate results.

Lawrence et al., (1985) tested the application of judgemental and statistical techniques in both the long – run and short – run periods, for seasonal and non-seasonal data. They found, that overall, there was no significant difference in the accuracy of either of these approaches, and both were not very accurate. In this case it should be noted that the authors used students as proxy experts for their experiment, and these participants may therefore have lacked domain knowledge of the products, thereby removing the potential advantage of judgment in a situation where statistical methods were performing badly.

However, even if forecasters possess domain knowledge, they may require assistance in using it in the forecasting task. One of the very few studies exploring judgemental approaches versus quantitative methods in new product forecasting was performed by Astebro and Koehler (2007). Their general assertion, based on previous studies was that statistical forecasting instruments are far superior to judgemental methods - only experts' forecasts, made in a highly structured way can give results comparable to statistical methods. The reason is that experts are not able to decode predictive cues in available information unless they are highly experienced. The authors examined experts' forecasts of the commercial potential of new products. They were given a large set of sales data and asked to use their judgment to predict future sales. They found that intuitive judgement is inevitably exposed to bias and tends to distort the forecasts, resulting in wrong predictions. In order to avoid such bias, the authors proposed a highly structured, systematic way of forecasting, and achieved about 80% correctness in predicting cases. The same data set was also used to make predictions by means of a statistical tool - an optimal linear statistical prediction model, and a 98% forecasting accuracy was achieved, which is still higher than it was obtained by the judgmental method.

3.3.3 Availability of the latest information

In a dynamic environment access to the latest information is likely to have a crucial effect on the relative accuracy of judgmental forecasts. Winklhofer and Diamantopoulos (1996) explored 11 companies and their forecasting practice. Some companies used quantitative and some qualitative methods for forecasting. Most companies used a quantitative approach, mainly naïve extrapolation (although one organisation used exponential smoothing), for short term forecasts.

As expected, in general, short-term forecasts were found to be more accurate than long-term forecasts. For the long term forecasts, none of the companies used quantitative methods; but instead relied only on experts' opinions. In this case, for example, one firm performed forecasts by intuitive judgement and reported "not very accurate" results for the short term forecasts, however all firms had "fairly accurate" results for the long term forecasts. The authors also reported that experts in the companies that obtained "more accurate results", by the judgemental approach, were constantly updated with the latest information. Alexander (1995) also found in a field study that the availability of up-to-date information gives advantage to analysts' judgemental predictions. Hence, to achieve success in judgemental forecasting, it is important for analysts to have updated contextual information.

However, other researchers found that even after being provided with new information, forecasters do not make substantial changes to their original opinions (Phillips and Edwards, 1966; Tversky and Kahneman, 1974). Thus, the ability of experts to use available data also is crucial in obtaining accurate forecasts. Remus et al. (1995) found in his research that people actually over-react to immediate past information and, as a result, judgemental forecasts are worse than forecasts from simple statistical models.

Sanders and Manrodt (2003) also pointed out that it is important not only to have up-to-date information but also to appropriately use this information. They classified available information as '*subjective*' (relating to rumours and unquantifiable information, such as competitor actions) and *'objective'* ones (facts), but in the real world it is very difficult to separate subjective and objective information. Unreliable information can lead to predictions being in the wrong direction. Rumours about emerging competitive products on the market may be phoney, but adjustments based on that information may well result in under stocking and subsequent customer dissatisfaction.

Mozes (2003) suggested that forecast accuracy also depends on the speed with which analysts respond to available information, thus the quicker the analysts respond to the information available the more accurate forecasts they produce.

And in the contrary, if analysts delay responding to the information and making relevant adjustments it will cause detrimental effects on accuracy.

However, Isiklar et al., (2006) investigated how contextual information was adopted by experts to perform GDP forecasts and found that it took 2 to 5 months to incorporate 90% of all new information. Therefore, analysts may simply not have that much time to include all the relevant information, or being able to distinguish the crucial information, which is most important to include into the relevant adjustments.

3.3.4 Stability and environmental uncertainty

Sanders and Manrodt (2003) found from surveys they carried out that the companies that are focused in judgemental forecasting methodologies had a higher MAPE (namely in excess of 20%), than the firms using quantitative methods which are reported to have a MAPE of within 5%. However, it seems that the different companies may have been working in environments that differed in their levels of uncertainty and stability.

For example, in another study Sanders and Ritzman (1991) found that during periods of constancy, quantitative methods worked better than qualitative, but expert judgement gave more accurate results than quantitative approaches in predicting the magnitude of temporary changes, the onset of temporary changes and the duration of changes. As a conclusion, they recommended a "switching rule", when managers interventions should be made when uncertainty grows while preference should be given to quantitative methods at the time of stability. The authors suggested being cautious with generalisation of their research outcomes, since during their research they used experts with high level of expertise and the experts made forecasts only for a few time series. A potential problem with this approach, hence, may be in dealing with habitual bias, described earlier. Also, people may assume that conditions are stable, if there has been such a condition during a long period of time, although changes are imminent. Moreover, in a competitive environment stable conditions are highly unlikely.

In summary, statistical methods are recognised to be more accurate when conditions are stable, although stable conditions may be perceived subjectively. In turn, more sophisticated quantitative tools are recommended to be used in order to achieve higher accuracy. Judgement can be advantageous in that it can recognise changes in the data pattern and external variables, which have predictive power, such as marketing and economic data. However, researchers agree that even though contextual knowledge is important, forecasting accuracy is also subject to the expert's ability to recognise and use information. Bias in judgement, as was discussed earlier, is also a factor which has a high hampering effect on prediction validity. In order to overcome these drawbacks, many researchers recommend that judgemental forecasting should be applied in a highly structured way.

While researchers discuss the pros and cons of qualitative and statistical forecasting tools, practitioners still prefer judgemental approaches, and their reasons for this relate not only to the predictive validity of the methods but to highly practical issues, such as the absence of statistical data and the need to have a "sense of ownership" of the forecasts. In the case of new product forecasting, as managers deal with high uncertainty and non-availability of historic data the qualitative approach will clearly be highly attractive to them.

3.4. An overview of judgemental techniques

Unaided judgement

Unaided judgment does not use the aid of any formal support mechanism to forecast, but makes the forecast by simply asking the experts to enumerate what will happen (Green, 2003). This method can work well if experts are unbiased and they receive up-to-date contextual information to take into account in their judgements. Feedback on the acceptability of the experts' forecasts can be an essential part of this method as it should help the experts learn and improve their forecasts. Judgemental predictions will be tend to be more accurate if made for short term and in a stable environment; in the long run, the forecasts are more likely to be inaccurate (Hogarth and Makridakis, 1981; Armstrong, 2001, Kahn, 2006) . However, given the limited information processing capacity of the human brain, it is likely that unaided judgmental forecasters will resort to the use of heuristics like availability and anchoring and adjustment and therefore will be subject to the biases that were discussed in section 3.2.

New product forecasting is associated with high uncertainty as there is no historic sales track available to serve as a benchmark for future tracking. This also means that there is little chance of supplying rapid and unambiguous feedback on performance, thus it is extremely difficult to make accurate judgements of the product's future demand. The forecasting literature (Fildes et al., 1978, Armstrong, 1985, Kahn, 2006) suggests that more advanced judgemental forecasting techniques, such as those reviewed below, are needed to help deal with the uncertainty associated with the New Product Forecasting and improve the accuracy.

Jury of executive opinion

This method is referred to as a 'non-formalised' method, which involves a meeting of experts to establish a forecast. Mostly, it is simply a judgemental extrapolation of past time-series trends accounting for the influence of external factors, such as competitor's actions, marketing plans and the economic situation. Many studies have revealed that people produce poor forecasts using this method. In particular, they tend to over forecast downward trends and under forecast upward trends (Lawrence, Edmundson and O'Connor, 1985; O'Connor, Remus and Griggs, 1997). This method is also prone to lead to biases caused by social pressures to conform (social pressure bias). For example, the influence of strong personalities dominating the meeting may lead to poor accuracy because a range of different perspectives is not considered.

Intentions and expectations surveys

Intentions are "measures of individuals' plans, goals, or expectations about what they will do in the future and are often used to forecast what people will do in the future" (Armstrong, 2001: 33). An expectations survey asks people how they expect to behave. Expectations differ from intentions because they take into account things that may happen due to the influence of external factors. Unlike the other judgemental methods in which the forecasts are based on the judgement of experts and managers, intentions and expectations surveys use the judgements of potential customers to produce demand forecasts. This approach is widely used in marketing due to the sense of assessing a “real attitude” of consumers towards the product. It also, allegedly, seems more objective because it excludes the bias of expertise and also biases like advocacy and optimism on the part of managers.

However, the method has many drawbacks. For example, people may change their intentions as time passes or it could be difficult for them to measure their intentions with certainty, since most of the intentions are contingent on many circumstances, such as financial affordability, fashionable trends, tastes, mood, availability of alternative products, accessibility (stores, on-line access), efficiency of advertisement and promotion, word of mouth and many others. Okun (1962) expressed doubts about this method, saying that the approach gives results which are no better than a simple mechanical extrapolation. In other words, this method is costly and it is unlikely that it will give objective estimations because consumers in these surveys give their present opinions and also they can not predict exactly their behaviour in the future.

Thomas (1985) revealed, moreover, that the results of intentions and expectations surveys depend on the way the surveys are conducted and how the questions in the surveys are structured. He explored 29 methodologies applied by 47 companies which operate in 30 different markets. He revealed that 85.2% or 23 /29 applications provided market-based estimates for demand evaluation, only 66.7% or 18/29 applications provided a survey tool to assess the purchase intentions and 44.4% or 12/29 methodologies provided no systematic demand estimating approach. He found that during the survey the assumed price did not include the cost of equipment, which produced the product, so the actual price of the product was higher than that indicated to consumers during the survey. As a result the survey suggested a higher number of potential customers, than the number who actually purchased the product, when it was marketed. Thus, questions need to be carefully tested in order to make sure that they are correctly formed and reflect the real situation. Estimations of market potential, performed through telephone interviews of organisations and household members also showed different results. He concluded that more research is needed to evaluate the validity and reliability of the market survey and intentions measurement methods and to compare them with other methodologies in new product forecasting.

Morwitz et al. (2007) also performed research to examine the validity of this forecasting approach. They established that intentions are in general better predictions for existing products rather than for new products, because greater familiarity with existing products helps consumers to estimate their likely purchase intentions (Goodwin, 2008). This method also has higher predictive validity for durable than for non – durable products, possibly because buying durable products (e.g. furniture) demands high consumer involvement in the purchase decision. Consumers are likely to know in advance if they will buy it or not, whereas buying non durable products (e.g. food) involve emotions, so the purchases are very likely made spontaneously. Morwitz et al. also found that this approach would better measure the trial rate of purchase (i.e., customers trying out a product for the first time) rather than total sales. Indeed, the first purchase does not guarantee repeat purchases. Estimations of intentions are also better when a consumer is able to compare the product in a survey with alternative products (for example, those of competitors'), otherwise the intentions during the survey will differ significantly from real purchase intentions. This method, certainly works better for short term forecasting, rather than for long term, since consumers can be surer of their intentions for a shorter period of time (Goodwin, 2008). This method is also costly to perform because the method involves people in getting the responses and, in most cases, it also needs preparation of trial specimens.

Therefore, this approach requires careful consideration of the survey execution process: how the questions are structured, what type of product is used, if alternative product choices are given, and the time horizon. Researchers are advised (Morwitz et al., 2007) to take into account other influencing factors on the purchasing decision, like accessibility of the product (availability in stores), the effectiveness of advertisements, changes in the economic situation and others. Morwitz et al., (2007) also suggested that this method would probably be better used in a weighted combination of forecasting models, where managers decide how much weight to be given to forecast obtained from intention surveys against the weight given to forecasts obtained in other models to get a final forecast through their integration.

Judgemental decomposition method

The basic idea behind judgemental decomposition is to divide the forecasting problem into smaller parts in order to simplify the judgemental task. Forecasts are made in relation to these parts separately, using methods appropriate to each part, these forecasts are then combined to obtain an overall forecast. For example, to forecast sales of a product in the market, one can estimate sales in each region or in each town or city separately and then reassemble the components together.

There are two forms of decomposition: additive and multiplicative (Armstrong, 2001). The additive approach relates to using segmentation in forecasting (for example, different types of food, like ice cream and milk dairies), by distinguishing independent components with individual causal factors, such as seasonality, age, family status. And then, the forecasts are aggregated into one prediction. In this example, milk dairy products normally would be sold to the sector of families with children and also can be sold to elderly people, but, probably, at the lower quantity. Thus, the estimated numbers of dairy products to families with children and to elderly people can be aggregated in order to obtain the whole milk dairies' prospective demand. Similarly, ice cream demand fluctuates during the calendar year with higher rate in summer. In order to obtain the whole year's demand, the estimates at different seasons are aggregated.

Multiplicative decomposition consists of multiplying components, for example, the whole market size for the product can be estimated (e.g. the whole UK yogurt market), then multiplied by the estimated market share for that particular product (e.g. Danon yogurts only) (Lawrence et al., 2006).

Empirical results indicate that, in general, forecasts from decomposition are more accurate than those from a holistic approach (Salo and Bunn, 1995). MacGregor and Armstrong (1994) found that multiplicative decomposition increases accuracy for problems with extreme and uncertain values. They also implied that decomposition is more useful for longer forecast horizons. However, there are also arguments against this approach. For example, Goodwin and Wright (1993) (in Lawrence et al., 2006) argued that accuracy can even decrease when decomposed judgements are more complex than holistic judgments and the procedure can become a tedious and time consuming exercise leading to deterioration in the quality of judgements. Armstrong et al (2005) also agree that decomposition can be risky because errors in the forecasting components multiply when the forecasts are recombined. Furthermore, when the errors in the forecasts of the components are in the same direction, the errors can be explosive: an increase of 20% in the forecast errors for two components translates into a 44% increase.

Kahn (2006) describes a method called *Assumption based analysis* as a tool for new product forecasting, which is highly similar to the judgemental decompositions method. This method takes into consideration of various scenarios regarding the market driving forces and makes future scenario predictions, based on these assumptions. Kahn (2006) gave an example of the ATAR (Awareness, Trial, Availability, and Repeat purchase) market driver model. In this method the estimated proportions of potential consumers under the influence of each of those components are multiplied to achieve the final prediction.
This approach (*Assumption based analysis)* gives a good opportunity to take into account marketing activity in sales forecasting. As Van den Bulte and Lilien (2001) noticed, ignoring consumer and market factors can seriously bias new product adoption estimations.

Managers may also learn from this model which factors are likely to explain the variation in demand and which events are likely to have an impact on the future growth of product sales. This would help them to improve decision-making and influence the quantity of demand by manipulating marketing mix variables. As this method is based on pure judgement we need either experts with high expertise or analogous product behaviour which can be used as a benchmark. In the case of using analogous product trends it would be difficult to discern what forces exactly influenced the trend of the product demand and in what manner i.e. supporting or opposing each other. The “double counting bias” can also occur, as described by Goodwin (2002), when the impacts of the drivers have already been accounted in the analogous product demand trend, but being unaware of it, experts may adjust the trend again.

In summary, it is clear that the judgemental decomposition approach can alleviate the demands of making judgements in complex situations and make it easier to understand the component parts of the problem. It also may help to identify and account for consumer and market drivers of new product adoption and hence give more accurate estimations. However, this approach does not always help to decrease judgemental bias and hence there is a high risk of obtaining wrong forecasts in any of the parts of the decomposed problem and arriving at a final result with an even higher rate of error than that of the holistic method.

Expert systems method

Expert systems forecasting involves identifying forecasting rules used by experts and rules learned from empirical research. In other words, the forecaster needs to learn how experts make predictions and make his or her own forecasts. An example of a forecasting expert system is software, which was developed by the National Aeronautics and Space Administration (NASA), this software uses rules, based on expert knowledge in the ’IF-THEN’ format (Flores and Pearce, 2000). There are rule sets, used in the forecasting expert system, such as: i) control rules (the systems gives rules for a user to make necessary settings), ii) early irrelevant data detection and adjustment rules (the system detects significant changes in the level of a time series and informs the expert about it, offering to re-consider changes), iii) outlier detection and iv) adjustment rules, v) trend verification rules (the software verifies if the trend type reported by the outlier detection rules is correct), vi) seasonality identification rules, vii) forecasting method selecting rules (the system selects the most suitable method viii) forecast generation, ix) the modification of forecast method rules (the system allows the user to choose a forecasting method), x) The modification of forecast values rules (the system allows the user to change values of variables in the forecasting method) (Flores and Pearce, 2000).

Learning the forecasting rules from the experts and formulating these rules into a rule base are time consuming tasks and they demand financial resources. Hence it is prudent to use this method when problems are sufficiently well structured and rules are easily identified, so the time spent and cost will be less.

Armstrong and Collopy (1998) described an akin method as a rule-based method, where the key aspect is a domain knowledge, which can be used to choose judgmental inputs into a statistical model. The forecasting models can also be chosen and adjusted by the judgment of experts. The rules represent instructions, which help to weigh the forecasts and obtain a final result.

The automated expert-system also saves time and effort and there is evidence that the forecasts produced by the automated system can be as good as those obtained by the system that allowed human intervention. Flores and Pearce (2000) compared two research systems, FP1 and FP2, between themselves and with other systems. FP1 made all the decision making automatically and in FP2 experts interacted with the system to make decisions. They found that the human intervention did not improve forecasting accuracy at all however the time and effort spent did increase substantially (FP1 took only half an hour while FP2 took significantly longer time). The authors did not describe fully the FP2 process, such as which experts participated in forecasting and how the decision making process was performed. As we know these factors are important in judgemental processes (Makridakis, 1981; Statman and Tyebjee, 1985; Wheelwright and Makridakis, 1985) and the absence of them make the assessment of the system difficult. Flores and Pearce (2000) also revealed that the expert systems performed ‘as well (or as bad)’ as other statistical methods that they used such as Naïve, Holt’s, Dampen and Box-Jenkins Automatic. In general, expert system forecasts are found to be more accurate than those performed by unaided judgement (Vokurka et al., 1996), but have similar accuracy to other econometric models.

The Delphi method

“The Delphi method is a group decision – making approach that is designed to gather subjective expert opinion through structured anonymous rounds of data collection” (Kahn, 2006: 11). It is designed to avoid the biases that often occur in open meetings such as social pressure bias. Armstrong (2001) suggests that under some circumstances the Delphi method gives substantially more accurate results than statistical approaches and individual experts. Chambers et al. (1971) also recommended this method from the perspective of accuracy. The method was developed as part of a U.S. military project at the time of the Cold War between the USA and Soviet Union, by the RAND Corporation. It was used to develop a strategic plan using a collection of expert opinions regarding the amount of weapons that were required (Tichy, 2004).

In general, there are five to twenty experts involved in this process. The process starts by polling them for their predictions and opinions. Then the experts' opinions are collected and statistically analysed and presented back to them as feedback, so they can adjust their estimates, if they wish. In some cases anonymous written discussion is also circulated. Sometimes the panel of experts can come to consensus in their opinions, and sometimes not. Rowe and Wright (1999) and Ashton (1985) argued that one of the aims of the Delphi method is to achieve agreement among experts. However, consensus of experts may not be necessarily the best outcome. In this regard, Story et al. (2001) stressed that achieving consensus by the Delphi panellists is not a primary goal; instead, this method can help to identify the reasons for disagreement. Usually, the median or mode of the final forecasts by the experts is taken as a final prediction. Even though there is another argument that averaging the opinions may also weaken the full forecasting validity because some of the predictions are inevitably inaccurate (Rohrbaugh, 1979).

The Delphi method has become a widely used instrument in making predictions in business. It has many advantages such as relative execution simplicity and the possibility of involving experts from different fields and backgrounds to express their opinion without the risk of being judged and psychologically influenced by other group members (Rowe and Wright, 1999). At the same time it is possible to give feedback and get people to adjust their predictions accordingly without the fear of losing face in front of other experts, due to the anonymity of the process Other advantages include its relatively low cost and the small amount of time the process takes, thus researchers (Rowe and Wright, 1999; Story et al., 2001) agreed that two rounds of the process is often sufficient to obtain valid results without creating boredom. As a result it is regarded as one of the most appropriate forecasting techniques in the hand of executive managers. This method also helps to collect expert's opinions without a personal meeting, so this frees up time and space and helps to avoid peer pressure and influence. It was found by several studies that this method outperforms unaided judgement and results obtained by other traditional judgemental groups (like the panel of experts or group discussions). Rowe et al. (2005) found evidence from previous work that the Delphi method outperformed statistical methods in twelve studies and outperformed other judgemental forecasting approaches. Landetta (2006) also analysed the publications which reported the use of Delphi method for forecasting in the last 30 years. He found that the method is widely used in practice and has a significant validity, however he did not find any strong arguments favouring or against the method, although comparisons with statistical methods and other classic judgemental groups (such as panel of experts) gave encouraging results.

This method has few weaknesses as well. Poorly formulated questions can result in inaccurate forecasts (Landeta, 2006). Restriction of communication between the experts may have a disadvantage of reducing the chances of exchanging information and tacit knowledge, which can lead to the overlooking of relevant information and, hence, to poor forecasting.

Among the variety of judgemental methods, arguably the Delphi method offers the most promise in new product forecasting. This method has also been widely used in practice and been favoured due to its simple, economic way of obtaining plural opinions in a short time. The method is recognised in its ability to reduce bias efficiently. However, it is an open question as to whether experts with rich domain knowledge have to be necessarily involved in Delphi or whether lay people can produce forecasts as successfully. This crucial point merits a closer look.

3.5. Selecting experts in judgmental forecasting

There is still some disagreement amongst researchers on the relative merits of obtaining forecasts from experts and novices, while some researchers posit that novices can predict as accurately as experts (Welty, 1972; Armstrong, 2001; Green and Armstrong, 2006), others (Hogarth and Makridakis, 1981); Statman and Tyebjee, 1985) have found that highly qualified experts' involvement improves accuracy. Wheelwright and Makridakis (1985) fairly suggested that experts need to have different backgrounds, which bring different perspectives to the forecasted product. Thus, in forecasting, it would be useful to have a panellist with specific knowledge of the product, and also people from marketing, management and other related areas. Story et al. (2001) summarised three general issues that need to be addressed to perform the Delphi method correctly, namely, i) there must be careful selection of experts, ii) clear defining of the research objectives (for this, they suggest using an unstructured or a semi-structured questionnaire in order to obtain the experts' ideas about the pertinent agendas to be included in the questionnaire) and iii) the researcher must have the ability to perform the study competently (to construct a correct and comprehensive questionnaire with impartial and objective approach). They suggested involving multiple researchers in the task.

Rowe et al. (2005) performed a study to reproduce and extend the earlier findings regarding the role of majority influence, expertise and confidence of Delphi panellists and they attempted to generalise their findings. They also agreed that the experts in a panel needed to be picked with care, since "better experts give better feedbacks" (Rowe et al. 2005: 396) by giving the reason for their opinion and any adjustments they might have carried out, thus allowing other judges to evaluate them. They also noticed that the researcher's ability to perform the research correctly has great importance. The framing of questions is important, since people tend to interpret and understand questions according to personal beliefs and values.

In contrast, Armstrong (2001) and Green and Armstrong (2006), found that experts' accuracy in prediction is usually little better than the forecast accuracy of novices. One of the reasons they mentioned, was that experts tend to be more confident in their estimations and do not explore the possibility of inaccuracy in their predictions. Similarly, Tetlock (2005) demonstrated, in a large study involving 82361 political and economic forecasts that experts performed worse than chance. However, they also demonstrated fine abilities to justify and defend their mistakes. While people are likely to believe experts, their advantage in forecasting in many domains is no more than an illusion and it is therefore difficult to assert that experts are better than lay people in terms of abilities to make better predictions. Forecasting ability may be simply narrowed down to an ability to use the accompanying information effectively. Although experts may still have advantages in knowing how certain dynamics will affect sales patterns, their overconfidence in their judgements may prevent them from objective analysis and considering other factors, which may also have crucial impacts on sales. Novices, on the other hand, being less confident, may consider all conditions and factors when they make their forecasts.

While heated discussions and debates go on about whether carefully performed subjective methods outperform objective ones or whether too much bias and uncertainty in expert opinions renders their forecasts less accurate than highly objective statistical methods, some researchers think that neither of those methods is superior and only their joint application may produce reasonable results. Indeed, even statistical methods inevitably require judgemental inputs when a forecaster chooses an appropriate statistical tool, inputs a statistical model's parameters or chooses a model's functional form.. Those manipulations need to be made using the forecaster's common sense or expertise, and will also be exposed to bias. But is the integration of quantitative and qualitative methods a solution to the issues discussed so far? This will be explored further in the next chapter.

3.6. Summary and conclusion

This chapter has reviewed the literature and empirical evidence on the importance and use of judgmental forecasting techniques in the new product launch process and compared the effectiveness of the approach with statistical methods. It revealed that judgmental forecasting is potentially important for new product launches because it allows prediction to be made in the absence of historic sales data. Judgment also considers contextual knowledge, which is important in unstable environments where there can be economic recessions or political instability. However, judgment is subject to bias and inconsistency due to forecasters' memory limitations and limited information processing capacity, which leads to error in forecasts.

Empirical studies over the last 20 years revealed that companies prefer judgmental techniques to statistical because of practical considerations, such as a lack of statistical data and lack of training in using statistic tools. Four techniques, "jury of executive opinions", "customer expectations", "decomposition" and "sales force composite" were mostly favoured and popular among the rest. Whereas, researchers, found out statistical techniques give higher predictive accuracy in stable environments, but when uncertainty increases, it is advisable to apply judgment. Judgment helps to recognise changes and allows the inclusion of external variables, which have predictive power. However, the availability of contextual information is not the only important factor in producing accurate forecasts. The expert's ability to recognise and use this information is also crucial. Bias is inherent in many judgments and hampers forecasting accuracy.

The analysis of judgmental forecasting techniques showed that one of the most accurate techniques, which helps to significantly reduce bias and is relatively simple to understand and perform, as well as having a low cost, is the Delphi method. This method help to avoid the influence of dominant people within groups and the integration of opinions helps to outweigh other sources of bias. Although it also has weaknesses, such as the inability of experts to share tacit knowledge, it is outbalanced by other strengths. Therefore, this method will be used for further testing to see if it can be used to generate better predictions of new product sales than purely quantitative methods or a combination of quantitative methods and judgment.

Finally, the value of choosing experts has been explored. The earlier research produced evidence that domain knowledge has crucial importance for new product forecasting, while recent studies have found that the greater predictive accuracy of experts is no more than an illusion and a result of their skills in convincing other people. To date, researchers have not come to a common conclusion on the value of experts in forecasting and this question remains open.

Chapter 4. Combining Quantitative and Qualitative methods of forecasting

The question of whether quantitative or qualitative forecasting methods generally lead to more accurate forecasts has never been resolved. In fact it seems that neither of the proponents of the two approaches can be ultimately right since different situations and cases require different approaches. For example, marketing people tend to use judgements in predicting the product’s future demand, while operations people mostly rely on quantitative approaches (Sanders and Ritzman, 2004). However, many forecasters have come to the agreement that a combination of the methods is most likely to improve forecasting accuracy (Makridakis and Wrinkler, 1983; Mathews and Diamantopoulos, 1986; Clemen, 1989; Sanders and Ritzman, 2004; Lawrence et al., 2006).

The following approaches exist to integrate quantitative and qualitative methods:

i) Judgmental adjustment of quantitative forecasts: this is common in managerial practice.
ii) Quantitative correction of judgmental forecasts: this reduces judgment's negative effect by identifying and eliminating systematic biases in judgmental forecasts.
iii) Combining judgmental and statistical forecasts: a combination of two independent forecasts (for example, by taking a simple average of the two forecasts).
iv) Judgmental choice of the inputs to *model building*. E.g. judgment could be used to select the variables for a quantitative forecasting model.

Each methodology has its strengths and weaknesses and needs to be carefully considered for its suitability in every individual case.

4.1. Judgmental adjustment of quantitative forecasts

This approach involves applying corrections and adjustments to the quantitative forecasts using judgment. It allows the forecaster to make necessary corrections in order to include influences of causal variables which may not have been incorporated into the statistical forecast. Numerous studies have been reported which explore the practical validity of using judgmental adjustments. While some earlier studies suggested that judgemental adjustments of a statistical model tend to improve accuracy (Carbone and Gorr, 1985; McNees, 1990) others (Carbone et al., 1983; Willemain, 1991) argued that judgemental adjustments increase forecasting error and need to be controlled. Some researchers have suggested that adjustment is the least recommended way to integrate methods, because of the possibility of increased experts' bias (Mathews and Diamantopoulos, 1986; Armstrong and Collopy, 1998; Goodwin 2000a, b). Sanders and Ritzman (in Armstrong, 2001) summarized the research in judgmental adjustments and stressed that managers should apply six principles when making adjustments. These are: i) adjust forecasts only if there is important contextual knowledge which has not been incorporated into the statistical model; ii) adjust statistical forecasts in situations with a high degree of uncertainty; iii) adjust when there are known changes in the environment; iv) structure the process; v) document all adjustments made and periodically relate the documented reasons for adjustments to forecast accuracy; vi) consider mechanically integrating objective and subjective forecasts rather than applying judgmental adjustments.

Goodwin (2005) added that one of the ways to decrease bias when a group of managers has to decide on a level of adjustment is to use the Delphi method rather than open group discussion. Sanders and Ritzman (2004) stated that adjustment should only be made when contextual information is available, however this assumes that the information used is correct. Remus et al. (1998) noted that the information may not necessarily be correct, and much of it may be informal information, such as rumours and gossip. They found that correct information, not surprisingly, led to increased accuracy of forecasting, while incorrect information gave no improvement in accuracy at all. They came to the conclusion however that forecasters can use information of unknown correctness without fear of having long term carryover effects on forecasts. Lim and O'Connor (1996) used postgraduate students in studying how people adjust statistical forecasts with available contextual/causal information. They found out that people tend to be conservative in their attitude to contextual information, and even though their final forecast was improved by including the information it was too slow and the adjustments were insufficient. In general, people were able to recognize important information with predictive power, but were nevertheless unsuccessful in adjusting their forecasts correctly. Goodwin and Fildes (1999), in another experiment involving student participants, found that people often have difficulties in recognizing the right cues for adjustments and often tend to make unnecessary corrections even when statistical forecasts provide excellent forecasting and ignore modifications when there is a good basis for adjustments. It may be that experts with high domain expertise are the best people to be involved in the forecasting procedure in order to recognize valid cues and estimate the size of necessary adjustments. Despite this, when Nikolopoulos et al. (2005) performed research on the adjustments of professional forecasters who possessed domain knowledge, they found that that 25% the adjustments were in the wrong direction while in 41% of cases the experts were overestimating actual sales. They also found that experts are over optimistic in assessing positive information. Consistent with this, in a recent paper, Fildes et al. (2009) found that positive adjustments were far less efficient than negative and forecasts tended to be overestimated. They also found that small adjustments mostly had detrimental effects on forecasts, while significant changes improved accuracy. This was due to the fact that larger changes were usually made on a basis of availability of reliable and important information while smaller changes were likely to be made due to other reasons such as the need to feel "a sense of ownership" of the forecasts (Goodwin, 2002) or simply a desire to demonstrate to more senior managers that the statistical forecasts were being examined conscientiously. Alternatively, the small adjustments may have resulted from forecasters falsely seeing systematic patterns in the noise associated with time series. This would be consistent with the use of the representativeness heuristic.

4.2. Judgment as input to model building

In this approach, "*an econometric or statistical model is constructed which uses a time series, and perhaps other causal variables, to produce the forecast*" (Webby and O'Connor, 1996: 99). Goodwin (2002) noted that, in fact, all forecasts involve judgment, for example in using judgment to choose a method, and a model form and causal variables, which influence sales trend, and therefore judgment is natural and indispensable (Lawrence et al., 2006) part of any forecasting activity. There are four ways in which judgment plays a role in the formulation of a statistical model (Bunn and Wright, 1991): a) causal variable selection, b) model specification, c) parameter estimation and d) data analysis. Indeed, even when statistical models, are used for forecasting, such as in regression analysis, cluster analysis and conjoint analysis, judgment can not be avoided in order to select relevant causal variables. The model itself needs to be specified by means of human judgment. Similarly, much of the output that is associated with statistical models, such as t-tests on model parameters or R-squared values may need to be assessed and interpreted judgmentally. As discussed earlier, in the case of diffusion models, parameters (such as market potential) and analogous products' sales data may need to be selected by using expert's opinion

There is some evidence that these judgmental inputs can be effective. For example, Sanchez-Ubeda and Berzosa (2007) used judgmental selection and modification of parameters of a statistical model to forecast natural gas consumption in Spain for short and long-term forecasting. They obtained results, which had an improved data fit of forecasted and actual results. Overall, this approach should be used when forecasters, in addition to having domain knowledge, have significant knowledge of quantitative techniques and an understanding of the quantitative procedure (Sanders and Ritzman, 2004). Again, while using judgment to determine inputs into the forecasting model, the judge's inherent bias may also have detrimental effect on forecasting accuracy.

4.3. Quantitative correction of judgmental forecasts

This approach aims to reduce judgment's negative effects by making quantitative corrections to judgmental forecasts. One of the ways to make statistical corrections of judgmental forecasts is through judgmental bootstrapping, when regression of the judgmental predictions is made against the causal variables, that were used for the predictions. The result is a model of how the judgmental forecaster has used the available information to make his or her forecasts. Forecasts from this model will tend to be more accurate than those of the original judgmental forecasts because the model allows ‘averaging out’ of the inconsistency of the forecaster. However, this approach has certain drawbacks (Armstrong, 2001) such as a requirement for more than 100 stimulus cases in order to obtain valid results.

An alternative statistical correction method has been suggested by Theil. This was described by Goodwin (1996). Theil’s correction model is obtained by the regression of actual outcomes on to the judgmental forecasts, as:

Formula 7. Theil's correction model

$$a_t = \alpha + \beta p_t + e_t ,$$

where a_t is the actual outcome at period t, p_t is the forecast for period t, e_t is a residual at t, *and* α and β are the population regression coefficients.

Then, the estimated regression coefficients can be applied to describe the corrected forecast for time t, $\hat{f}_t$, free of systematic bias, as $\hat{f}_t = \hat{\alpha} + \hat{\beta} p_t$, where $\hat{\alpha}$ and $\hat{\beta}$ are Ordinary Least Square (OLS) estimators of α and β.

Goodwin and Lawton (2003) discussed studies by Ahlburg (1984) and Elgers, May and Murray (1995), which supported the idea of using statistical correction for accuracy improvement. However, in changing conditions, e.g. when the forecast is made under the influence of some events such as a product promotion, or when simply a forecaster is replaced by another more or less experienced person the Theil’s correction method may reduce accuracy because it is correcting for biases that no longer apply. Thus, a discounted weighted regression (DWR) was proposed to be used in such conditions (Goodwin, 1997). This method involves giving lower weights to older forecasts, allowing the correction to adapt to changes in biases in the forecasts. The DWR method consistently gave more robust results than Theil’s method in the study by Goodwin (1997).

Obviously, statistical corrections have potential for reducing bias and hence the resulting errors. However, they are likely to have little use for new product forecasting, since no previous forecasts are available because of the absence of previous sales history. If a forecaster has produced sales forecasts for many earlier products then there might be sufficient data to measure the forecaster's biases and hence apply correction, but this situation is likely to be rare.

4.4. Combining judgmental and statistical forecasts

This method relates to the combination of quantitative and qualitative forecasts that have been derived independently. The rationale for the method is that the constituent forecasts in the combination will draw on different, and possibly complementary, information sources thereby enhancing the range of information on which the forecast will be based (Clemen, 1989). The approach has certain advantages over the other integration methods discussed above: it is simple to perform and the random errors inherent in the forecasts will be reduced because they tend to cancel each other out, which results in the improved forecasting accuracy (Armstrong, 1989).

The combination can be performed objectively (e.g. by simple averaging) and subjectively (contingent on specific contextual information) (Sanders and Ritzman, 2004). Webby and O'Connor (1996) concluded from earlier studies that combining methods leads in general to improvement in forecasting results, though mixed results have been found as well. For example, some studies found that simple averaging gives highly accurate results, while others provide some evidence that regression-based weighting (contingent on specific contextual information) is more accurate than simple averaging. They also noted that previous studies drew general conclusions about greater accuracy of the combination method without testing these results for statistical significance and hence these general conclusions can still be questioned. However, Goodwin (2002) emphasised that mathematically estimated weights (to be used in combining the qualitative and quantitative methods) require unbiased constituent forecasts, sufficient past data and a stationary pattern of forecast errors over time, which makes this approach practically impossible to perform accurately in many contexts, such as new product forecasting. Thus, in empirical application, combining is often reduced to simple averaging.

Sanders and Ritzman (1990) suggest that forecasts should not be combined when they vary in accuracy because the combination of predictions with lower and high accuracies will reduce the overall forecast accuracy. In reality, however, it is impossible to define at the stage of forecasting, which of the predictions is accurate and which is not. There is always a great chance that some experts will produce forecasts with superior accuracy compared to others. Overall, the results of research suggest that combination should be considered as a valid method to improve forecast accuracy.

4.5. Comparing objective and subjective integration methods in terms of producing higher forecasting accuracy

Sanders and Ritzman (2004) underlined the ideal criteria that should be met in the integration of objective and subjective methods in order to achieve best results: i) the subjective and objective forecasts have to be performed independently, ii) there has to be low correlation between the forecast errors of the different methods, iii) experts with domain knowledge need to be involved in the subjective forecasts or specific information, not counted in the statistical forecasts need to be used. In relation to this point they suggested that adjustment will improve forecasting if it is based on domain knowledge.

Goodwin (2000b) carried out a study to compare the accuracy of forecasts obtained through Theil's optimal linear correction with those obtained (i) by combining subjective and objective forecasts through simple averaging and (ii) by using both correction and combining in tandem. He obtained results, which revealed that there was little gain in making independent forecasts and combining them, compared to the simpler process of statistically correcting judgmental forecasts.

Lawrence et al. (1986) found that combining judgmental forecasts based on two methods of judgement always gave better accuracy in any forecasting horizon, long or short term, (the two methods involved extrapolating data that was presented either in a graph or a table). Moreover, the combination of three or four forecasts gives better accuracy than 2 combined forecasts. Consistent with other studies (Chambers et al. 1971; Lawrence et al., 1985; Armstrong, 2001) found that the combination of forecasts gave greater accuracy in the short run. They also suggested that the long term forecasting can be obtained accurately through the combination of given stable time series. Their research also gave support to the validity of bootstrapping models, showing that mechanical combination of judgements works better than intuitive combination.

Regarding judgemental adjustments of statistical forecasts, Armstrong and Collopy (1998) said that they are “risky” and suggested that judgement should be used as an input to statistical methods rather than used for ex post adjustment and it is better to produce a new forecast than revising the initial one, if someone wants to include information or correct errors. There is an additional danger of a double counting effect (Goodwin, 2002), when the factors used to justify adjustments have been already accounted in the statistical model (e.g. the forecaster may have a wrong perception that seasonality has not been incorporated into the statistical forecast). They concluded that adjustment can only be made if experts have good domain knowledge and judgements are made in a structured way. They stress that domain knowledge is the key factor to improving forecasts; it helps to identify causal factors, the functional form of the time series, and the presence of any unusual patterns. However, when experts have no rich domain knowledge, the selection of the integration approach is not critical.

There has been a number of research studies performed in combining forecasts by means of judgmental (weighed combination) and mechanistic (simple averaging) methods (Brehmer, 1980; Angus-Leppan and Fatseas, 1986; Lawrence et al., 1986; Goodwin and Wright 1994; Webby and O’Connor, 1996).

Brehmer (1980) made an argument that people in judgmental tasks cannot accurately determine probabilities in the judgment accuracy. As discussed earlier expert judgments are inevitably influenced by various sources of bias, including conservatism bias, when people are prone to give heavier weighting to their own judgement and are reluctant to change it even in the light of new information or put more weight to someone’s opinion, which matches their own rather than spending time to consider other alternative opinions.

Goodwin and Wright (1994), Webby and O'Connor (1996) summarised a number of experimental works of the role of judgment in forecasting and concluded that research to date favours simple averaging over weighed combination on the basis that practitioner ought to use averaging in order to minimise error in combined forecasts.

Lawrence et al. (1986) also found consistent results that simple averaging outperformed judgmental combination due to the fact that random noise incorporated in judgment create highly distorted results, therefore averaging produces lower error. The research results of Angus-Leppan and Fatseas (1986) showed that the mean absolute percentage error (MAPE) of the judgmentally combined forecasts was marginally greater than that of the individual forecasts due to the aggregation of errors in forecasts.

Fischer and Harvey (1999) also compared simple averaging with judgmental combination, giving structural feedback to the experts after the first round of the forecasts performance. The found results, which reinforced earlier statements of Lawrence et al. (1986) and Goodwin and Wright (1994) about the adequacy of using simple averaging for forecasts combination in order to reduce random error.

As summarized by Armstrong and Collopy (1998), in the case of a high degree of uncertainty (which relates to new product forecasting) the simple combination of different forecasting methods has the potential to enhance accuracy.
Therefore this approach will be justifiably used in this research.

4.6 Summary and conclusions

Statistical and judgmental approaches to sales forecasting both have advantages and disadvantages and often these complement each other. For example judgmental forecasters can suffer from cognitive biases while statistical forecasts may have an ability to account for rapid changes in the external environment. As a result many researchers agreed that the integration of these methods is likely to give better results than either of them independently. There are roughly four ways of integrating of objective and subjective methods, such as, judgmental adjustment of quantitative forecasts (the most commonly used in practice), quantitative corrections of judgmental forecasts, combination through averaging or regression-based weighting and a final method, application of judgment as input to a quantitative model building.

Judgmental adjustment is recommended only if domain knowledge is available and measures to overcome judgmental bias, such as obtaining forecasts by means of the Delphi method are undertaken. Judgment as an input to model building, is probably, part of any forecasting activity because it involves judgmental choices of forecasting models, parameters estimations, causal variables selection and finally, data analysis. The disadvantage is that forecasters using this approach need to have significant knowledge of statistical techniques in addition to domain knowledge.

Quantitative corrections of judgmental forecasts have been explored by researchers through judgmental bootstrapping or Theil's statistical correction. The first approach although being simple to perform requires over 100 stimulus cases in order to receive valid results and the latter approach would rather be suitable for those with sophisticated knowledge of statistical instruments. It has also been found that forecasting accuracy improvement obtained through statistical adjustment is similar to that received by means of simple averaging of independently performed quantitative and qualitative forecasts and in some cases, simple averaging even produced results of higher accuracy. Another way of combining is a regression based weighted combination, when weightings to the combined parts are assigned according to the estimated accuracy they deliver before combining them. This approach, require unbiased constituent forecasts, sufficient past data and other features, which makes the process practically cumbersome and foster manager's preferences for simple averaging.

It has been highlighted earlier that in case of a new product forecasting, where uncertainty is high and often, domain knowledge is not readily available, especially in cases of a new to the world product development, simple averaging and judgmental revisions are equally helpful.

Therefore, for practitioners, the easiest method, given proven accuracy, would probably be a simple averaging of independently performed statistical and judgmental forecasts even though the statistical forecasts themselves have already involved a combination of judgment and statistics. The discussion in the earlier chapters suggested that the most favorable methods for managers, in terms of simplicity, are the Bass model as a statistical tool and the Delphi method as a judgmental method of forecasting. But does their combination give better accuracy for a new product sales forecasting and, if so, by how much? This question remains unresolved and merits further research, which will be described in the following chapters.

Chapter 5. Methodology and Empirical testing

5.1. Methodology identification based on ontology and epistemology of the phenomena

The present appraisal is concerned with providing a justified rationale for the selection of a research methodology, deemed appropriate for academic research that is chiefly quantitative in nature. Indeed, the call for appropriate academic research may arise when there is a need to address gaps in a certain body of literature, or a need to offer reliable solutions to real life business predicaments (Bryman and Bell, 2011; Saunders, Lewis and Thornhill, 2009). Invariably, academic researchers engage in a deliberative and purposeful process (Blumberg, Cooper and Schindler, 2008; Bryman and Bell, 2011; Saunders et al., 2009). In particular, this process "involves situating business research in the context of the social science disciplines, such as sociology, psychology, anthropology, and economics, which inform the study of business and its specific fields, which include marketing, HRM, strategy, organizational behaviour, accounting and finance, industrial relations, and operational research" (Bryman and Bell, 2001: 4).

Blumberg et al., (2008) explain how the ways in which empirical research is undertaken is rooted in the wider philosophies of knowledge. In particular, the authors explain how research is primarily grounded by reason, commonly referred to as theory, alongside observation, to include empirical findings and information. Still, in order to develop knowledge, the way in which observations and one's approach to thinking are interconnected persists as hot topic of debate (Blumberg et al., 2008; Collis and Hussey, 2003).

To develop knowledge, Johnson and Duberley (2000) explain that even though the domains of science and philosophy have deliberated upon the enquiry of epistemology, (and dating back to the times of Plato as well as Aristotle), epistemology persists as a rather curious mystery for the vast majority. Thus often charged with seeming to obscure more than what it makes known, in order to clarify its meaning, "The word derives from two Greek words: '*episteme'* which means 'knowledge' or 'science'; and '*logos'* which means 'knowledge', ‘information’, ‘theory’ or ‘account’. This aetiology demonstrates how epistemology is usually understood as being concerned with knowledge about knowledge” (Johnson and Duberley, 2000: 2). Subsequently, epistemology may be understood as a way to convey a theory-driven perspective of knowledge (Johnson and Duberley, 2000), as well as a ‘reason to believe’ (Audi, 2011).

In contrast to ‘epistemology’, another major way of ‘thinking’ is that of ‘ontology’ (Saunders et al., 2009; Thiétart et al., 2001). “Ontology is concerned with the nature of reality. This raises questions of the assumptions researchers have about the way the world operates and the commitment held to particular views” (Saunders et al., 2009: 110). Objectivism and subjectivism are the two predominant pillars of perspective for understanding ontology; objectivism preaches the stance of independence and separatism, whereas subjectivism advocates the recognition of social meaning and perceptual interpretation (Bryman and Bell, 2011; Saunders et al., 2009).

In fact, objectivism is seemingly on a par with positivism, whereas subjectivism is on a par with interpretivism (Blumberg et al., 2008). To explain, in social science research one’s selection of an appropriate process of gathering empirical data is marked by these afore-mentioned research paradigms/ philosophies: (i) positivism, and (ii) interpretivism; the latter also commonly referred to as phenomenology (Collis and Hussey, 2003; Johnson and Duberley, 2000; Morgan and Smircich, 1980). Situated between these two apparent extremities, a range of alternative philosophical teachings exist, which incorporate some perspectives of either a positivist or interpretativist philosophy, to include for example, ‘realism’ (Blumberg et al., 2008).

Primarily, positivist viewpoints encompass the more observable, measurable and quantifiable perspective, which is framed by objective, scientific and experimental traditionalism (Collis and Hussey, 2003). In contrast, interpretivism is seemingly more qualitative, subjective and humanistic in approach (Collis and Hussey, 2003). Please refer to the table below for a comparison of the two extreme research paradigms.

	Positivism	Interpretivism
Basic Principles		
View of the world	The world is external and objective	The world is socially constructed and subjective
Involvement of researcher	Researcher is independent	Researcher is part of what is observed and sometimes even actively collaborates
Researcher's influence	Research is value-free	Research is driven by human interests
Assumptions		
What is observed?	Objective, often quantitative, facts	Subjective interpretations of meanings
How is knowledge developed?	Reducing phenomena to simple elements representing general laws	Taking a broad and total view of phenomena to detect explanations beyond the current knowledge

Source: Blumberg et al., (2008).

With reference to the above table, the wider study at hand is concerned with the forecasting of statistically quantifiable data. Therefore the prevailing aim of the research is to forecast sales data that is essentially characterised as quantitative in orientation. Hitherto, in considering the quantitative leaning of the prevailing study, it is somewhat apparent that positivism is the most appropriate research philosophy to adopt. As a point of comparison, interpretivism is driven by a greater sense of exploration and speculation, designed to build and contribute new theoretical contribution, as opposed to test and develop theoretical contributions already established. Hence, a key parameter to accommodate when designing research is to ascertain how the liaison interconnecting theory and one's research seemingly operates (Bryman and Bell, 2011).

In fact, one needs to consider whether one's approach is to be primarily 'deductive' in style, that is, the theory serves to direct the research, or alternatively whether one's approach is 'inductive in style, in that the theory is more a product of the endeavour of research (Bryman and Bell, 2011; Collis and Hussey, 2003). Subsequently, to fathom the ways in which knowledge can be developed by the present study, the real key to research therefore is not necessarily a matter of whether the endeavour is 'philosophically informed' so to speak, but more so a matter of how well a researcher is able to be reflective upon one's philosophical choosing, as well as be capable of providing a justification for the chosen selection compared to the other philosophically-immersed alternatives (Johnson and Clark, 2006; Saunders et al., 2009).

In fact, "The research philosophy you adopt contains important assumptions about the way in which you view the world. These assumptions will underpin your research strategy and the methods you choose as part of that strategy. The researcher who is concerned with facts, such as the resources needed in a manufacturing process, is likely to have a very different view on the way research should be conducted from the researcher concerned with the feelings and attitudes of the workers towards their managers in that same manufacturing process. Not only will their strategies and methods probably differ considerably, but so will their views on what is important, and perhaps most significantly, what is useful" (Saunders et al., 2009: 108).

Still, the development of knowledge remains relentless through time in its ability to provoke persistent philosophical debates (Blumberg et al., 2008). One main reason for why is that some idea of underlying philosophical considerations not only helps to clarify the research process, but it also facilitates the selection of a suitable research design (Blumberg et al., 2008; Thiétart et al., 2001). For example, in light of the wider study at hand, when evaluating the process of research, a common distinction made in terms of research strategy is that of whether a quantitative or qualitative tact is deemed preferable (Bell and Bryman, 2011; Johnson and Duberley, 2000; Bryman, 1993). As the present study is primarily steeped in providing value-free measurements and observations of factual data that espouse an objective ontology guided by theory, a more quantitative angle is evidently preferred (Bell and Bryman, 2011).

In conclusion, the present appraisal advocates the value of adopting a positivist perspective to manage the way in which the present research endeavour is framed. Therefore, rooted by theory-driven epistemology and an objective ontology, positivism is a more appropriate approach for the present study, as it is particularly concerned with data that are statistically drawn and quantitative in nature. For this the practical experiments will be carried out to on existing sales data of target and analogous products and quantitative analysis (using statistical instruments) will be used to measure and compare the relative accuracy of a range of forecasting methods based on the analogies.

5.2. Background to the research

The literature review revealed that the Bass diffusion model is widely used in new product forecasting and that it offers the advantages of being relatively simple while also providing an explanation for the performance of new products via the coefficients of imitation (p) and innovation (q). This should make it attractive to managers. If the Bass method is applied in a 'purely' statistical way, avoiding for example, the judgmental estimation of 'p' and 'q', then it requires data on the sales history of analogous products that have been launched earlier than the product for which forecasts are required (the target product). The estimated 'p' and 'q' values derived for the analogies can then be applied to produce forecasts for the target   This raises the issues of i) how suitable analogies can be identified and ii) whether it is worth using average parameter values from several analogies. If the forecasting method is 'purely' statistical then the identification of appropriate analogies will also be based on statistical methods.

However, the review also revealed that integrating management judgment with statistical methods can lead to enhancements in forecasting accuracy. In particular, it has been argued that judgmental inputs to statistical forecasting methods are indispensable. But where are judgmental inputs into the Bass modelling process likely to be most valuable? It seems that expecting managers to use their judgment to estimate accurate values for 'p' and 'q' is likely to be unrealistic as the values may not be meaningful to them and sufficient information to support such judgments is unlikely to be available. Similarly, estimates of the market saturation level (m) are likely to be best obtained from market research which uses consumer intentions surveys, despite the problems with this approach outlined earlier. In particular, judgmental estimates of 'm' are likely to be distorted by advocacy and optimism bias. However, it is possible that judgment can play a useful role in the identification of suitable analogies for the Bass modelling process. In this research it is investigated whether the use of judgment to identify analogies for the Bass models leads to greater accuracy than statistical identification. Because the literature review suggested that the Delphi method can be effective in enhancing the quality of judgments, it was used as the basis for the judgmental identification of analogies.

An alternative approach to the use of a small number of close analogies to identify appropriate parameter values for a Bass model is to use data on a wider range of products, for example all products in a particular industry. The mean parameter values for all of these products might provide suitable values for the target product. However, data on these products can also be used to obtain regression models which explain variation in the values of parameter values between products. These models can therefore be employed to produce forecasts of the parameter values for target products based on their characteristics. The effectiveness of this approach will be compared with those outlined earlier.

This leads to the following research questions:

1. Does the statistical identification of analogies based on product characteristics lead to more accurate forecasts than: a) using industry average parameter values and b) using randomly selected analogies?

2. Do human judges, participating in the Delphi method, select more appropriate analogies than statistical methods?

3. Does the combination of 'purely' statistical forecasts and forecasts based on the judgmental selection of analogies lead to improved forecast accuracy?

5.3. Measuring the accuracy of a sales forecasting model

A large number measures are available to measure the accuracy of forecasts. From previous works in measuring forecasting accuracy (Fildes and Goodwin, 2007/2005; Ilonen et al., 2006; Goodwin, 2000; Flores and Pearce, 2000; Lobo and Nair, 1990; Lawrence et al., 1986; Makridakis and Wrinkler, 1983) it can be inferred that the most popular error measures used by researchers are the MAPE (Mean Average Percentage Error) and the MSE (Mean Square Error).

The formula for the MSE is

Formula 8. Mean Square Error (MSE)

$$MSE = \frac{\Sigma(A - F)^2}{n}$$

where n = number of forecast errors, A = the actual value and F= the forecast

The MAPE is calculated as follows:

Formula 9. Mean Average Percentage Error (MAPE)

$$MAPE = 100 \times \frac{\Sigma|A-F|/A}{n}$$

where 100* |A-F|/A is referred to as the absolute percentage error or APE.

The MSE is recommended by some researchers to be used as an error measure because it provides a relative stable measure of forecast accuracy (Armstrong and Lusk, 1983). However, the MAPE is favoured by managers (McCarthy et al., 2006; Mentzer and Kent, 1999) because it indicates the importance of the forecast error in relation to the volume of sales - a forecast error of 2 units is likely to be of concern when the volume of actual sales is 10 units, but of little concern when the sales volume is 10,000 units. Moreover, the MSE is difficult to interpret due to its squared values. The MAPE also is reported in most of the published studies (Armstrong, 1983). For cross series comparison, which is to be performed in this research, the MAPE is also more appropriate, because it is less affected by extreme errors than the MSE (Lawrence et al., 1986).

The MAPE was intended to be used as the main forecasting accuracy measure in this research. However, in new product sales forecasting the measure has a major potential disadvantage. This occurs because the APE involves dividing the absolute forecast error by the actual sales, In the early years of a product’s life its sales are likely to be low. Hence high APEs tend to occur in forecasts for these early years (e.g. an error of only 2 units on an actual sale of 1 unit yields an APE of 200%). This tends to distort the measurement of the forecasting method's accuracy.

In the context of new product forecasting it is therefore more reasonable to use MdAPE (Median Absolute Percentage Error) as the error measure in this research. This is because it reduces the bias in favour of low forecasts by trimming the effect of the extreme APEs associated with low actual sales (Armstrong, 1992).

However, it is worth noting that MdAPE measure will still be influenced by sets of APEs which can be extremely high when actual sales are very low in the early years following a product's launch. This may be an advantage if the early sales are likely to be of most interest to managers, perhaps because they will be crucial in deciding whether the marketing of a new product should continue for a sustained period.

Nevertheless, this measure will have a distorted reflection of the accuracy of forecasts over a product's entire life. Therefore, an additional error measure has been developed in attempt to make an assessment of the typical accuracy of forecasts over the entire life of a product, avoiding the generation of extreme APEs caused by low actual sales. This is a measure called the modified mean absolute percentage error (MMAPE) will be used. This involves the calculation of the APE as follows:

Formula 10. Actual Percentage Error (APE)

$$\frac{100 \times |\text{Actual sales} - \text{Forecast}|}{\text{Mean sales over observed life of product}}$$

It can be seen that the means sales over the observed life of the product replaces the actual sales for each individual period as the denominator.

Therefore, two measures: the MdAPE and the MMAPE will be used in this research in order to enhance the *construct validity* (construct validity relates to the extent to which the measures used in the study accurately measure a specified construct, which in this case, is forecast accuracy).

5.4. Data sampling and preparing for the analysis

Because the availability of data for this research depends highly on the willingness of companies to provide such data or the possibility of purchasing them from database companies, the data could only be gathered through convenience sampling. In other words, data was used, which was most available or accessible, given budgetary and access constraints. Data requests were sent to a number of companies and eventually electronic product data was purchased from the Consumer Electronic Association (CEA), the leading trade association supporting the growth of the electronics industry in the United States of America (www.mycea.ce.org). The data package contained annual sales data of 97 electronic goods, such as TV, radio, CD players, headset audiphones, cellular phones and many others, launched commercially on the US market during the period between 1946 and 2007.

5.4.1 Data preparation

Among the data obtained, all products with a commercial life of less than 5 years (i.e. having data for less than 5 time periods) were excluded from the data as the number of observed periods was insufficient for the application of statistical forecasting methods.

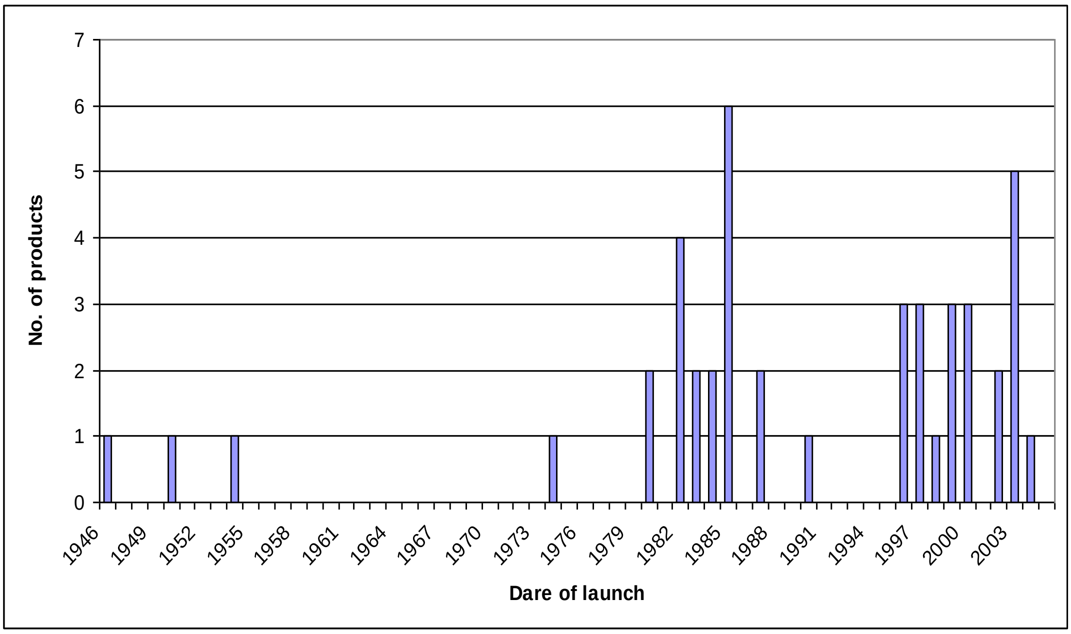
This measure is justified by the likelihood of fluctuations in early data in the diffusion process (Wright, 1997) .This may result from the fact that firms are still operating in experiment mode during this early period following the product launch and improvements to the product and its marketing may still be taking place (Tigert and Farivar, 1981). Bass (1969) suggested that the starting period for analysis should be the first period when actual sales are greater than or equal to 'pm'. However this approach in estimating the minimum data required is practically inapplicable, since 'p' changes tend to fluctuate with every new data added to the data base (Van den Bulte, 1997), therefore this process is somewhat circular. As an alternative Wright (1997) carried out a research, applying the Bass model to telecommunication products and found that the model requires at least three periods to estimate the diffusion curve adequately. In particular he found that some products, such as walkie-talkie the number of required data points were 2-3 and for others, like cellular and other products required 5-10 data points. He (Wright, 1997) also found that using fewer data points (1-2) lead to the underestimation of the timing and the magnitude of the sales peak.

For some unnamed telecommunication products, three periods of data produced adequate results of defining the diffusion curve, however it resulted in negative values for p and m. Therefore in this research a minimum of 5 years data needed to be available in order to reduce the risk of invalid results.

Products where zero sales were recorded for each year of the product's life were also removed. In addition, there were a number of products where the algorithm used to estimate the parameters of the Bass models (this will be described later) yielded negative p and q values. These products were also removed from the analysis. In most cases graphs of the sales of these products suggested unusual patterns that did not conform to the usual S-shaped curve. Eventually 44 products were left from the initial data set. It is important to stress that, only products from the analogies data base were removed. No target product was removed because it it failed to conform to a Bass model. This is sensible as a forecaster would be able to filter out these untypical potential analogies before producing forecasts for the targets. Therefore, this manipulation did not affect the results generalisability by any means or the validity of the approach.

A decision then had to be made regarding which products should be designated as analogies and which as target products. The analogies had to be such that they were i) launched earlier than the target product and ii) had generated sufficient sales data to allow a Bass model to be fitted before the launch of the target product. Figure 3 shows the launch dates of the products used in the analysis. It was decided that products launched before 1995 would be used as analogous products while those launched after 1995 would be designated as target products. This meant that there were 21 target products and 23 analogous products.

Figure 3 The products' dates of launch



5.4.2 Fitting the Bass models to the analogous products

Bass diffusion models were fitted individually to each analogous product's sales. Only sales data up to 1995 was used. This was to ensure that only data that could have been known on the date of a target's product launch was used in the forecasting process. In order to estimate the Bass model parameters ('p' - the coefficient of innovation or external influence, q' - the coefficient of imitation or internal influence and 'm' –the saturation level) the following procedure was used

1. First the OLS (Ordinary Least Squares) method, described in Franses (2009) was applied.

OLS was used to fit the following model to the annual sales data:

Formula 11. OLS fit to annual sales data

$X_{n+1} = \alpha_1 + \alpha_2 N_n + \alpha_3 N_n^2 + \varepsilon_{n+1}$ where,

X_{n+1} is the sales for year n +1

N_n is the cumulative sales up to year n

The last term in the model is the residual for year n +1 and the α_i are parameters estimated using OLS.

After obtaining estimates of the α_i, starting estimates of p and q were derived by solving the following equations:

Formula 12. Starting estimates of p, q, and m

$$\alpha_0 = pm$$

$$\alpha_1 = q - p$$

$$\alpha_2 = q/m$$

The values of 'p', 'q' and 'm' obtained here were only treated as starting estimates because of the limitation of OLS that were referred to in Chapter 2. The purpose of obtaining the starting values was to provide initial estimates that were likely to be close to the optimum values, thereby reducing the danger that the non-linear least squares procedure, that was subsequently used, would terminate at a local, rather than a global minimum.

2. Micosoft Excel's Solver facility was then used to obtain 'final' estimates of p, q and m, based on the starting values determined in stage 1 and with the objective of minimising the MAPE of the fitted model.

5.4.3 Using the analogous products to forecast the sales of target products

Forecasting the sales of target product, based on a given analogy involved using a Bass model with the 'p' and 'q' values that had been estimated for the analogy. When several analogies were used the mean 'p' and 'q' values of these analogies was used to forecast sales for the target. However, because the scale of the sales levels of the product exhibited a large variation it did not make sense to use the 'm' value estimated for the analogy to produce forecasts for the target. For example, if an analogy had a saturation level (m) of 1,000,000 sales units, forecasts for a target with a potential value of m of 1000 would be highly inaccurate if the analogy's saturation level was used in the forecasting model. Such variation in 'm' values, even between similar products, might be expected over time because of different economic conditions and changes in market sizes. In practice the value of 'm' for a product can be estimated using other devices such as intentions surveys or population levels.

To take this into account Bass models were fitted to the sales of the target products, using the method described above, and the value of 'm' was estimated. This value of 'm' was used alongside the analogy's 'p' and 'q' values to produce forecasts for the target products. Thus the analysis described here assumed that a good estimate of 'm' was available at the time of the product's launch, which may or may not be the case in practice. Nevertheless, other researchers (e.g. Lilien et al., 1999; Van den Bulte and Lilien, 2001) have also recommended that 'm' should be determined outside the modelling process. Where a good estimate of 'm' cannot be obtained the error measures presented later may overestimate the accuracy of the forecasting methods being considered. However, as it will be argued later, these methods were being tested in a situation that may be more challenging that that which applies in many company contexts so any overestimation of accuracy may be mitigated to some extent.

Chapter 6. Applying statistical approaches to the identification of analogies

6.1 Benchmarks for accuracy from previous research

Before assessing the effectiveness of statistical approaches to new product forecasting based on analogies it will be useful to establish some benchmarks, which will provide guidance on what level of accuracy can be expected in new product forecasting. The benchmarks will also provide an indication of the degree to which forecast errors are unavoidable or are due to an inability to select appropriate analogies.

Kahn (2006) explored the average accuracy rates in new product forecasting for different types of 'new' products, i.e. 'new-to-the world', 'product improvement', 'product line extension and others', and found that forecasts for those types of products led to accuracy in the range of 40% -71%. Unfortunately, Kahn did not define his accuracy measure. If we assume that the accuracy he reported could represented by MdAPEs, and given that in this present research some products belong to the 'new-to-the world' type of products, such as Monochrome TV, introduced in 1946, while others could be identified as 'product improvements', such as cordless telephone (an improvement on the corded telephone), then the median MdAPE magnitudes listed in Kahn's (2006) study is around 58.5%. It appears from Kahn's paper that this accuracy level was obtained by the means of various forecasting techniques, such as statistical, judgmental and the combinations of them and the measure of accuracies are averaged across the forecasting results of 49 interviewed companies.

Rao (1985) compared forecasting performances of various diffusion models (i.e. the Mansfield Model, the Floyd Model, the Martino Model, the Bass Model, the Nonuniform Influence Model, the Lekvaal & Wahlbin Model) and Trend extrapolation models (The Linear Model, Quadratic Model, Exponential Model, The Gompertz Trend Model, The Naïve I Model), among which the Bass diffusion model produced forecasts with MAPEs in the range of 31.3% – 80.2%, with an average accuracy of around 60%. Those forecasts were performed for various high technology products, such as room air conditioners, dish washers, clothes dryers and colour TVs. The trend extrapolation models produced generally better results than diffusion models with the lowest MAPE 6.2% and the highest 44.5%, however the author stresses that this could be due to the existence of simple patterns in the data and one needs to be cautious to compare the performance relative to those models.

However, it is important to stress that none of the forecasts in these two studies involved the use of analogous products. Instead, they were extrapolations based on the early sales data and hence did not relate to brand new products. Arguably, such forecasts should lead to more accurate results than those obtained in this research where there is no information on early sales patterns.

6.2 Benchmarks for accuracy based on electronic products in the purchased database

Apart from the benchmarks, obtained from previous research it has been mentioned earlier that benchmarks, obtained from the current data analysis will also be used to estimate how well the new product forecasting can be performed, based on the statistical, judgmental approaches and the integration of them.

Thus, the second set of benchmarks is presented here which assume different levels of information availability at the time of the forecasts. These provide guidance on how much deterioration in accuracy is accounted for by the absence of that information (see below):

1. *Optimum sales trend fit*: Suppose that at the time of the forecasts the sales of the product are actually known so that we can fit the optimum Bass model to the data (using Excel Solver). As described earlier (section 5.2) MdAPE and MMAPE will be used as accuracy measures in this research. Thus, if the optimum model is used, then the mean and median of the MdAPEs and the MMAPEs for all the target products will be as shown below (Table 1):

Table 1. Optimum sales trend fit results

	MdAPEs	MMAPEs
Mean	16.15	13.35
Median	14.35	13.44

The results, as seen from the table suggest that mean absolute percentage errors of average sales around 13% would still be expected even if the 'best' Bass model could be fitted to the future sales. This error reflects the fact that no Bass model can exactly describe the sales pattern of a product.

The possibility that sales growth does not conform to the structure represented by the model can contribute to this error, as can the fact that strictly the Bass model is designed to represent adoption rather than sales. Replacements and multiple purchases will thus cause sales to deviate from the model.

2 *Best analogy*: If it was possible to always identify the best analogy for each product so that the most accurate forecasts were obtained, (i.e., analogy yielding the lowest MdAPE or the lowest MMAPEs was selected) then the Means and Medians of the MMAPEs and MdAPEs would be:

Table 2. Best analogy results

	MdAPEs	MMAPEs
Mean	26.43	30.36
Median	24.29	25.79

For this, all 23 analogous products were to perform forecasts for each of the 21 target products and the analogy yielding the greatest accuracy for each target was selected. Its p and q parameters were used to predict sales for the target product.

The results show that even if best analogy could be identified, mean APEs would still be as high as 26-30%, therefore, it is likely that no analogy among those available for this research will be a perfect model for the sales of a new product.

3. *Selecting a single analogy or multiple analogies at random:*

An Excel macro was used to carry out 1000 simulations each of which involved selecting a product randomly from the database of analogies and using its p and q values to produce forecasts for each target product in turn. The averages of MdAPEs and MMAPEs of all the forecasts were then calculated and these are shown below:

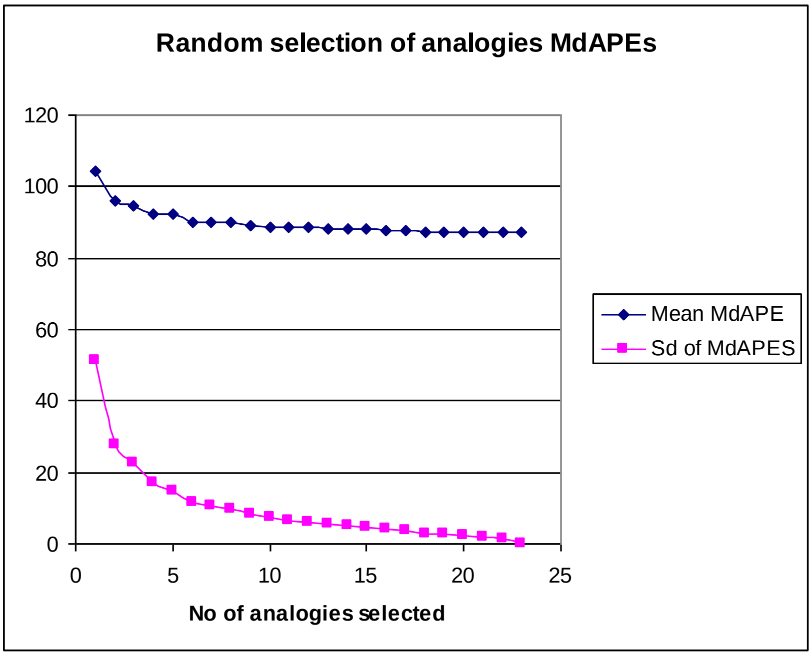
Table 3. Selecting a single analogy or multiple analogies at random results

	MdAPEs	MMAPEs
Mean	102.60	78.72
Median	71.25	66.95

The results are much higher (by around 48% on average) than those obtained by choosing a best single analogy (above), which shows the potential value of selecting a good analogy rather than selecting any of the products randomly.

To investigate whether accuracy gains are likely to be achieved when more than one analogy is selected at random, the above simulation was repeated for 2 to 23 analogies. In each case the mean p and q of the selected analogies were used to produce forecasts for the targets. Figure 4 shows the results. It can be seen that taking the mean p and q values of the entire set of 23 analogies produces the most accurate forecasts. However, there are few gains in average accuracy to be made beyond the selection of about 6 random analogies (the decrease in MdAPE beyond this point was insignificant, see Figure 4), though the level of risk associated with any given selection continues to be reduced substantially for higher samples sizes (this is shown by the standard deviation of the MdAPEs which approaches zero as the number of randomly selected analogies increases).

Figure 4 Random selection of analogies



If the mean p and q values of all of the 23 analogies are used then the following results are obtained:

Table 4. All analogies 'p' and 'q' used results

	MdAPEs	MMAPEs
Mean	86.45	56.05
Median	50.35	59.45

4. *Using 'p' and 'q' estimates from previous studies*: In order to compare the results with those of the previous researches, related to this domain, the 'p' and 'q' values for electronic products, determined by Lilien et al., (1999) were used and averaged in order to obtain forecasts for the target products in this research. The Mean and Median of MdAPEs and MMAPEs of the forecasts produced by this approach are shown below:

Table 5. Using 'p'and 'q' estimates from previous studies results

	MdAPEs	MMAPEs
Mean	249.90	95.07
Median	89.06	67.80

This suggests that relying on published average ‘p’ and ‘q’ values for an industry can lead to highly inaccurate forecasts.

6.3 Statistical forecasting based on analogies: Method 1

As was discussed in the literature review, in order to carry out sales forecasting on the basis of analogous products, a structured analogies method is recommended. For that, the data identifying the products’ features were collected and analysed in order to identify product similarities in a structured way.

The initial analysis used the following variables for which quantitative data was available:

1. The date of launch of the product

2. Average days work required to purchase product in years 1 and 4 of its life.

Since the products under consideration had dates of launch spread along the decades between 1954 and 2007, the nominal variable ‘Price’ would not represent a valid variable, since it changed due to the influence of factors, such as the economic situation. For example, 10 US dollars in 2000 did not have the same purchasing value as 10 US dollars in 1954 due to currency inflation. In addition, the incomes of potential customers have changed substantially over these years. Therefore, price has been replaced by the ratio “Average days, required to work in order to purchase the product”. The ratio has been quantified as below:

Formula 13. Average days required to work in order to purchase the product

$$\frac{P * N}{S}$$ Where,

P - product price

N - The number of working days in the year

S - The average salary per year (Source: Social Security Online, 2011)

In order to enhance the ability of the approach to capture price change dynamics, this ratio has been taken for two time periods: the first year of the product launch and for the fourth year after the product launch.

To identify the analogies, cluster analysis based on the hierarchical clustering method and the squared Euclidean distance measure was decided to be used in order to identify the ‘closest’ product in terms of the above variables. All of the products, both analogies and targets, were used in the cluster analysis. Cluster analysis is a data analysis tool which allows sorting different objects into groups with the maximum degree of association between objects (Abonyi and Feil, 2007). This method is widely used in management science for selecting similar objects (Li and Rue, 2007; Slater and Olson, 2001; Galbraith and Schendel, 1983).

In this research the method allows grouping the analogous products, which have most similar prices (average days, required to work in order to purchase the product) and dates of launch. In order to perform this test in SPSS, the values were standardised by Z-scores.

For each target product the analogy which had the smallest squared Euclidean distance from the target was identified as the closest analogy. The previously found ‘p’ and ‘q’ parameters, for the analogous product were substituted into the Bass diffusion model to produce sales forecast for the target. MdAPEs and MMAPEs were used as indicators of forecasting accuracy, as described earlier.

In case of identifying one best single analogy the Nearest Neighbour approach was applied. Many researchers (Kaufman and Rousseeuw, 2008; Lance and Williams, 1967; Punj and Stewart, 1983; Fraley and Raftery, 1998) have elected to use Euclidean distance, when the smallest distance between the products in clustering is taken to define the nearest neighbour (Lance and Williams, 1967), and in this case, the best analogy.

The accuracy obtained by using a single, closest analogy to produce forecasts for each target product is shown below (the forecast horizons lie in the range of 6-13 years).

Table 6. Method 1 (using 1 best analogy) results

	MdAPE	MMAPE
Mean	122.11	74.46
Median	66.22	66.28

The table shows that on most of the measures the accuracy obtained though this process is little better than that obtained by selecting a single analogy at random (see section 6.2) (e.g. the mean MMAPE is 74.46% compared to 78.72% for the random strategy). Indeed, the mean MdAPE for this process is actually much higher than that of the random strategy.

6.4 Statistical forecasting based on analogies: Method 2

This method is similar to Method 1, except that the three closest analogies to each target were identified, rather than the single closest analogy. The use of three analogies was recommended by Thomas (1985). The mean p and q values of these three analogies were substituted into a Bass Model and this was used to produce sales forecasts for the target product. The results are shown in the table below.

Table 7. Method 2 results (using 3 best analogies)

	MdAPE	MMAPE
Mean	170.04	143.69
Median	48.82	54.30

The differences between the mean and median rows revealed that extreme MdAPEs and MMAPEs have severely distorted the mean when three analogies were used. However, the statistical comparison of the MdAPE values for 1 and 3 analogies (The Wilcoxon signed rank test) showed no significant difference between the median MdAPEs (p-value = 0.29). No significant difference also was found between the MMAPEs (p-value = 0.346). Therefore, averaging parameters of the best three analogous products did not yield any improvement in accuracy.

Thomas (1985) performed empirical tests on averaging diffusion model parameters, similar to the present research, and obtained predicted values 25% higher than actual sales. In this research the results showed median a MdAPE of 48.82% and a MMAPE of 54.3%. There are several possible reasons why the parameter averaging did not yield forecasting improvement, or results as accurate of those of Thomas. These include:

1) The use of an insufficient number of variables to identify similar products (only 3 variables were used here)
2) Inappropriate variables being used in the identification
3) The forecasts were performed for quite long periods of time (up to 13 years), using analogous products with the dates of launch going back to up to 53 years. The diffusion parameters were assumed to remain constant over the time also, which may not be the case (this possibility will be examined later).

6.5 Statistical forecasting based on analogies: Method 3

6.5.1 What makes a good analogy?

The poor performance of the analogy-based forecasting methods described in the previous section raises the question of what makes a good analogy or what product characteristics need to be identified in order to find the 'best' analogies in order to obtain improved forecasts? According to Blanchette and Dunbar (2000), analogies can be identified according to superficial features as well as by deeper underlying structures. The authors reviewed 20 years of research findings in human psychology, and found that this suggests that people tend to use superficial features to identify analogies, while the good analogies tend to be those, which have very similar deep structural features. Thus, perhaps, the best analogy for a High Definition TV in terms of sales pattern will not be necessarily a colour stereo TV, but, for example, a fax machine, which may have a very similar deep underlying structure, such as similarities in its price, the level of the need for it amongst potential consumers and its degree of innovativeness.

To check this possibility, a brainstorming analysis among the researchers (the writer of this thesis and her two academic supervisors) was used to identify the closest analogy or analogies to the target product using the product's structuring features beyond those identified in the previous section. As a result of the discussions it was suggested that the following characteristics might be relevant:

1. The level of threat of product substitute at the year of launch (high, low)
2. Whether or not the product is portable
3. Whether or not the product was highly useful/compelling, so it could not be substituted and was unique in the sense of practical application. For example, a personal answering device or a blank audio cassette.
4. Whether or not the average time before the product was replaced with a new version was less than or equal to 5 years
5. Whether or not the major function of the product is to record still and moving pictures
6. Whether or not the primary use of the product is to facilitate live two-way communication between at least two parties
7. Whether or not the primary function of the product is to allow user to both to record and playback music
8. Whether or not the primary use of the product is to supply entertainment produced by a party other than the user
9. Whether or not the product would be useful to a typical small business.

For these characteristics myself and my two academic supervisors first independently assessed both the analogies and the targets for the presence or absence of that characteristic. Any differences between these assessments were subsequently resolved through discussion at a meeting.

6.5.2 Use of these characteristics in forecasting

The characteristics identified above were represented as dummy variables where a value of 1 indicated that the characteristic was present and 0 that it was absent. These data were combined with the three quantitative variables used in the previous analysis (date of the product launch, income per price ratio at the first year of product launch and the fourth). The most similar analogies, based on these variables were identified using a distance measure known as Gower's similarity coefficient (Gower, 1971). This distance measure was used because it allows similar objects to be identified when the observed data has different types of variables (categorical, binary and continuous).

The analogous products identified by this approach were then used to obtain forecasts for the target products, using one best analogy (identified by the smallest Gower coefficient). The results were obtained as below:

Table 8. Method 3 results (using more product characteristics)

	MdAPE	MMAPE
Mean	105.48	66.88
Median	62.05	64.27

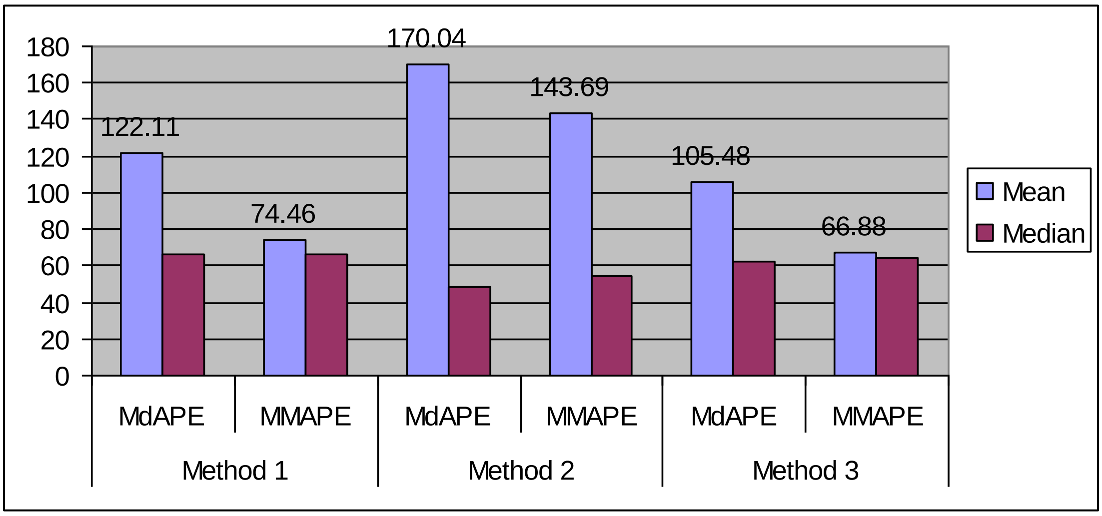
A non-parametric statistical analysis, used Friedman's test to compare the accuracy of this method with that, obtained by the methods 1 and 2, revealed no statistically significant difference between any of the 3 methods (p-value=0.921).

Table 9. Comparing Methods 1, 2 and 3 results

	Method 1			Method 2			Method 3	
	MdAPE	**MMAPE**		**MdAPE**	**MMAPE**		**MdAPE**	**MMAPE**
Mean	122.11	74.46	**Mean**	170.04	143.69	**Mean**	105.48	66.88
Median	66.22	66.28	**Median**	48.82	54.3	**Median**	62.05	64.27

However, figure 5 suggests a slight increase in the accuracy when method 3 is used (lower mean MdAPE and MMAPE).

Figure 5 Comparing 3 methods



The fact that only three people were used in the brainstorming for method 3 may suggest that there were not enough number participants to decrease biases and lead to significantly more accurate results compared to the other methods (1 and 2). Further research, involving a larger number of participants may give different results.

6.6 Summary

First, an attempt to achieve a perfect sales data fit by the means of Bass model reflected the fact that no Bass model can exactly describe sales pattern. Second, it was revealed that a potential value exists in finding a best possible analogy rather than picking an analogy at random. Also, if no effective method can be found in identifying a best analogy, it is better to use the averaged parameters of all analogies that are available. It was also found that finding a single best analogy statistically yields accuracy results similar to those obtained by averaging parameters of three best analogies.

Comparing these results to previous studies, the methods 1 and 2 yielded similar results to those found by Kahn (2006) and Rao (1985), although none of them used analogous products for forecasting, and worse results than those obtained by Thomas (1985), who also used analogous product data.

These results lead to the question “What actually makes a good analogy?” An attempt to identify the products’ deeper underlying structure was made and although the results did not reveal a statistically significant difference it may be a reasonable basis for future research in testing this method with a bigger number of participants in identifying the products underlying variables judgmentally.

The next chapter examines, whether the judgmental approach in determining the best analogous products will result in better forecasts than the statistical approach.

Chapter 7 Using the Delphi method to identify analogies

Judgment offers an alternative to the use of statistical methods in the identification of analogies. The literature review indicated that the Delphi method can be a particularly effective way of obtaining reliable judgments as it uses the judgments of more than one person, but also avoids the possible biases that are often associated with judgments made by groups of people. In this chapter an experiment is described, which was carried out to see if the use of the Delphi method to identify suitable analogies led to more accurate sales forecasts of the target products than the statistical methods that were explored in the last chapter.

7.1 Implementing the Delphi method

Implementing the experiment to test the effectiveness of the Delphi method involved the following steps, as recommended by Adler and Ziglio (1996):

1. Twelve Delphi panels were formed
2. The first round Delphi template was developed.
3. The template was tested (e.g. for ambiguities, and vagueness).
4. The first templates were transmitted to the panellists.
5. The first round responses were analysed.
6. The second round templates were prepared.
7. The second round templates were transmitted.
8. The results were aggregated and analysed.

7.1.1 Formation of Delphi study several panels

As discussed in Chapter 2, researchers have not come to an agreement on whether experts outperform lay people in making accurate predictions judgmentally. Moreover, in practice it is not always easy to find experts in the required domain areas. From another perspective, hiring lay people may provide some advantages too, since the diversity of experiences and expertise enhances a group’s strength in terms of the ability to consider various conditions and make judgments from different perspectives. It was also concluded that a minimum of about 5 members would be enough for creating a panel of forecasters.

Eventually, 12 panels, each with 4-6 members (lay people), were created by recruiting people to identify the best analogous products for the target products. Participants were allocated to the panels randomly. Among the panel members, MBA and PhD students were recruited as well as professionals with different backgrounds. In total, 52 people were participating in the survey. The participants were asked to make their judgments anonymously and separately from each other. As a motivating factor, two money prizes for the best efforts in judgement performance were offered, and small cash rewards for students were offered for participating in the survey.

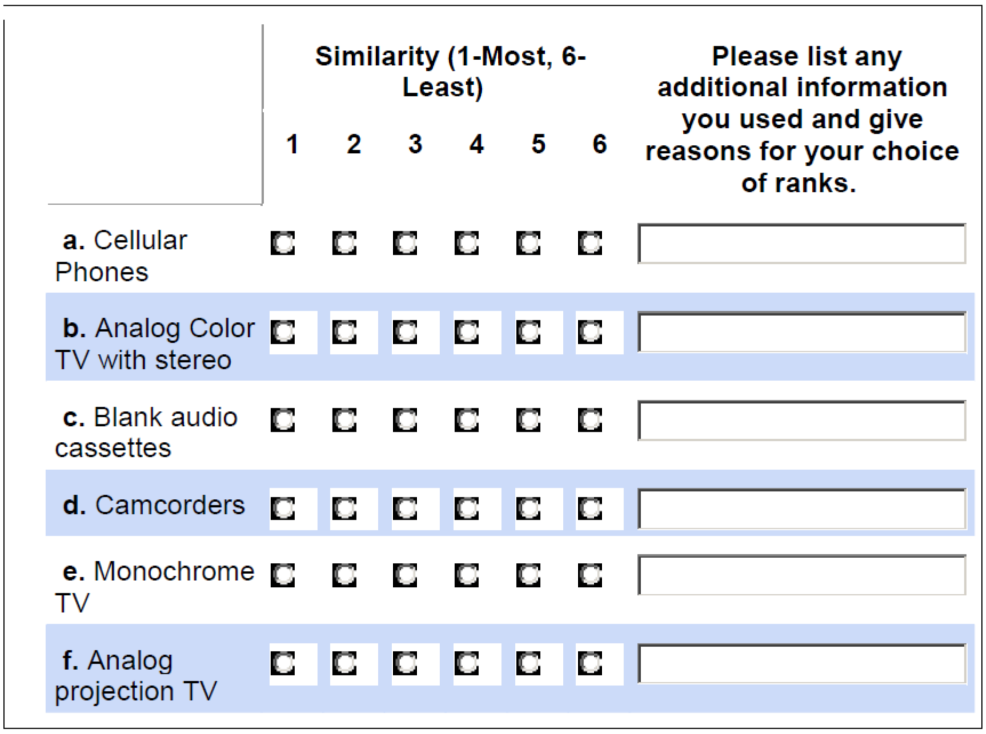
7.1.2 The Delphi template outline

The survey was organised on-line, using the Bristol Online Surveys software (www.survey.bris.ac.uk/) in order to provide privacy for the participants, and enhance the speed and financial economy of the project. Ideally, using the range of all analogous products for each target product to identify the best analogies would improve the results validity, however, since there were 21 target products and 23 analogous products, this process was practically infeasible due to the time and resources constraints available for this research. Therefore, in order to balance the maximum number of analogous products to be tested for each of the target products with the maximum time, the respondents could reasonably devote to the Delphi survey, 6 possible analogous products eventually were chosen for each target product in each of the 12 Delphi surveys. Each of the twelve Delphi exercises contained 7 target products.

The analogous products were carefully selected so that their characteristics varied in their degrees of similarity with the target products on variables such as 'application' (e.g. televisions: Colour TV, Monochrome TV) and differences in the ‘launch dates’ between the analogy and the target product. For example, for the target product, Digital front projection TV (launch date - 2002) a “worst” analogy might be Monochrome TV (launch date - 1946) while Analog Color TV with stereo (launch date - 1984) might offer a “best” analogy. For each target product 2 "best", 2 "medium" and 2 "worst" analogies were chosen. An example of such selection is given on the figure below.

Figure 6 Delphi test questionnaire example

Target product: Digital front projection TV



	Similarity (1-Most, 6-Least)						Please list any additional information you used and give reasons for your choice of ranks.
	1	2	3	4	5	6	
a. Cellular Phones							
b. Analog Color TV with stereo							
c. Blank audio cassettes							
d. Camcorders							
e. Monochrome TV							
f. Analog projection TV							

As the picture shows, participants were asked to rate the similarity of each analogy to the target product for the purpose of sales forecasting on a 1 to 6 scale (1-least similar, 6-most similar) (Adler and Ziglio, 1996).

The six-point scale in the Delphi survey was used because the task involved ranking 6 available analogous products in similarity to the target product. Therefore, the most similar product was ranked as '1' and the least similar product (out of 6) was ranked as '6'.

The respondents were provided with an information package, which contained:

i) The aims of the survey
ii) A description of the procedure to be followed
iii) Rewards information

iv) An indication that additional information to support their judgments was available on request.

This additional information included:

i) The products' dates of launch, days required to work to buy the product, and the product's category ('new to the world' versus 'an improved version of a previous product')

ii) Descriptive information for the product and references to web links, where a picture of the product could be viewed.

Participants were also informed that they were free to use any other relevant information they might find and which they felt might be important.

An example of the task instructions is shown below:

Please rank the potentially analogous products that are listed, in order of their similarity/analogy to the target product.

Please use, if necessary, the information provided, which contains:
a) data of the product launch date
b) the product category, which means if the product was new to the world or just an improved version of the predecessor
c) the number of days required to work in order to purchase the product, which reflects the sense of the product price in the first and fourth years after the product launch.

In the provided boxes please give reasons for your ranking (i.e. what information was helpful to make judgments).
Feel free to use any additional information you have which you think will be helpful in making your judgments. In such case please list the information you used too.

You may also find more information about the products by pressing the "More Info" button.

1. Target product: DVD Players/Recorders

DVD player is a device that plays DVD discs under both the video and audio technical standards.

VCR Decks

VCR deck (Video Cassette Recorder) player/recorder combined in one set.

Rack Audio Systems: An audio equipment available in a rack mountable version.

Videocassette Players: Unlike the VCRs (Video Cassette Recorder) Videocassette player is used for playing back only video images and sound on a videocassette.

Telephone Answering Devices: An answering machine, also known as an answerphone (especially in the UK and some Commonwealth countries), and sometimes/formerly telephone answering device (TAD), is a device attached to a telephone and could be set to record a voice message from a caller.

	Similarity (1-Most, 6-least)						Please list any additional information you used and give reasons for your choice of ranks.
	1	2	3	4	5	6	
a. Corded Telephones	☐	☐	☐	☐	☐	☐	
b. Home Radios	☐	☐	☐	☐	☐	☐	
c. VCR Decks	☐	☐	☐	☐	☐	☐	
d. Rack Audio Systems	☐	☐	☐	☐	☐	☐	
e. Videocassette Players	☐	☐	☐	☐	☐	☐	
f. Telephone Answering Devices	☐	☐	☐	☐	☐	☐	

7.1.3 Ethical issues

Privacy: The participants or panel members were able to work at any time, convenient for them. They also had rights to withdraw at any time from the research.

Confidentiality: It was not compulsory for the participants to give their names, only contact e-mails were used to identify them.
All the data obtained for the research were treated as being strictly confidential and were used strictly for research purposes only.

Data access and ownership: Only the researchers had access to the data obtained and these were not revealed to any third party.

7.1.4 Testing the template

In order to present the information used in the survey clearly (i.e. instructions, information and requirements), and to minimise ambiguity, the survey was pre-tested with some volunteers.

The pre-test participants were asked to complete the survey and give their opinions about the clarity of the instructions, time they spent completing it, the complexity of the task. They were also asked to give feedback regarding any improvements or amendments that they felt were necessary. This feedback was used to improve the clarity of expressions and to detect missing information or cases of ambiguity in interpretation by the participants.

7.1.5 Carrying out the Delphi experiment

The template then was transmitted to the survey participants by providing them a web link to the survey (www.survey.bris.ac.uk/). After 4 weeks all the responses were collected and analysed. The responses were summarised for each panel and the product ranks were organised and averaged when necessary (for example if 50% of respondents gave rank 1 to the product, and the other 50% ranked it as 2, the averaged rank was 1.5 = (1+2)/2). For each panel, the potential analogies for a target product were then ranked according to their average ranks from the first round (e.g. if the average ranks of products A, B and C were 1.5, 2.5 and 3, respectively then they were ranked as A:1, B: 2 and C: 3) These ranks were then fed back to all the panellists together with their own responses from the first round and they were asked to reconsider, their responses. The format of the questions in the second round was the same as that used in the first round. Four weeks later, the second round responses were collected and analysed. The whole process of the Delphi survey took about 3 months in total to complete and there were 2 iterations in total (1 per each round).

7.2. Analysis of Delphi survey results

Predictions of sales for the target products were made using the ‘p’ and ‘q’ values of the “best” analogous product, chosen by each Delphi panel. The results are shown below.

Table 10. Delphi survey results

	MdAPE	MMAPE
Mean	96.54	70.83
Median	73.85	69.83

Before comparing these results with those in the previous chapter it is important to recall that only a subset of the target and analogous products were used in the Delphi study.

In order to evaluate how the Delphi panel performed the MdAPE and MMAPE of predictions, made on basis of all analogous products available to each panel were calculated. In other words, forecasts for each target product were performed using every analogous product in turn, offered in the survey. For example, below it is shown which products were offered in the survey to choose from as a best analogy for a target product - Telephone Answering Devices.

Telephone Answering Devices

a. Corded Telephones

b. Home Radios

c. VCR Decks

d. Rack Audio Systems

e. Videocassette Players

f. Telephone Answering Devices

Thus, the forecasts for Telephone Answering Devices were performed assuming that the panellists were unable to discriminate between the analogous products provided to them and ranked them all as equally similar to the target, Then the averages of the resulting MdAPEs and MMAPEs were calculated and these are shown below:

Table 11. Averages of all analogies available to panel

	MdAPE	MMAPE
Mean (all analogies available to panel)	104.26	69.79
Median (all analogies available to panel)	73.04	69.78

In contrast, had the Delphi groups always identified the best analogy and given this the highest rank then the following results would have been achieved.

Table 12. Results 'if best analogy was always chosen'

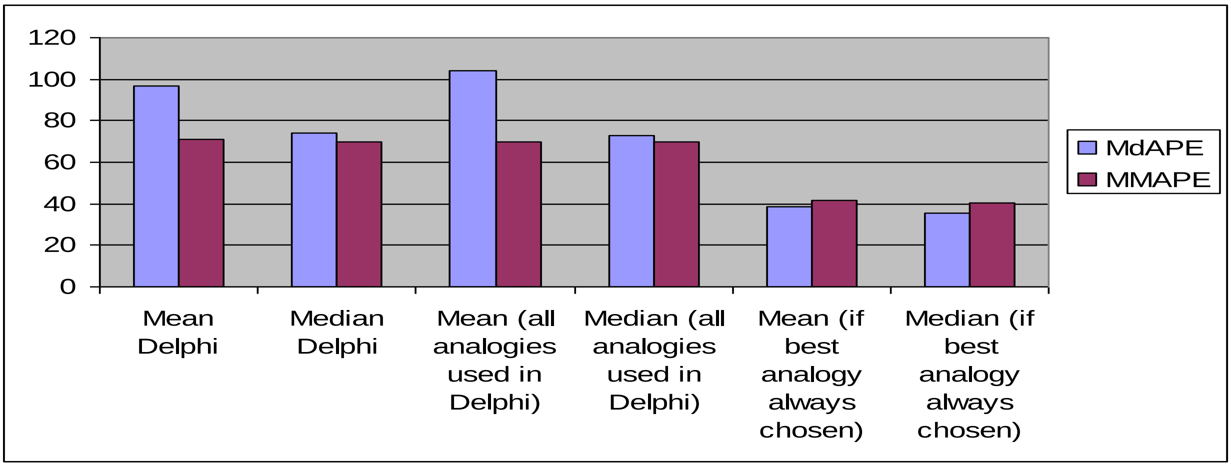
	MdAPE	MMAPE
Mean (if best analogy always chosen)	38.38	41.86
Median (if best always chosen)	35.32	40.60

These results show that there is no evidence that the participants in the Delphi study were able to identify the best analogy. The forecasts that they generated were no more accurate than those that would have been expected had they randomly selected the highest ranking analogy from those provided. The results also show that there was considerable scope for obtaining relatively accurate forecasts had the participants been able to identify the best analogy. However, they were unable to this.

The graph below summaries the MdAPEs and MMAPEs that we have just discussed.

Note that, in general, the MdAPEs and MMAPES have close values.

Figure 7 Results obtained by Delphi test involvement



Although the Delphi experiment only involved judgmental inputs to the forecasting process via the selection of analogies (the Bass model was used to produce the actual forecasts themselves) it is interesting to compare these results with earlier studies in judgmental sales forecasting. Thomassey and Fiordaliso (2006) researched textile apparel mid-term forecasting using analogous products as well by the means of a judgmental approach, namely decision trees, and obtained an average MAPE around 195% and a MdAPE around 108.5%, which are higher than the results obtained in this research. The lowest MAPE and MdAPE were obtained by means of the C4.5 (a type of a program for Machine Learning) (Quinlan, 1993 in Thomassey and Fiordaliso, 2006) decision tree algorithm system, and were 126% and 66% respectively, which are somewhat close to the results of this research). It should also be emphasised that these results relate to 'mid term' forecasting and so, unlike the work reported in this thesis, early sales figures for products were already available to the forecasters.

Lawrence et al. (2000) have researched judgmental forecasting accuracy in 13 companies for durable and non-durable products. These products were also established, rather than new, so greater forecasting accuracy might have been expected. However, they found that the average MAPE the companies for all the products was 129.92%.

Therefore, it is seen that findings in this research (Mean MdAPE = 96.54, mean MMAPE = 95.92) are somewhat consistent to previous researches in using judgmental forecasts in sales forecasting and even slightly better since the average MAPE (96.54) is lower than MAPEs from those researches as described above.

This may, of course, reflect the use of the Bass model in the forecasts rather than the quality of judgment per se.

7. 3. Combining the Delphi-based forecasts with statistical forecasts

The literature review suggested that in the case of high uncertainly, which is intrinsic to new product forecasting, the simple combination of different forecasting methods can produce more accurate forecasts than either method used on its own (e.g. see Goodwin, 2002; Armstrong and Collopy, 1998; Webby and O'Connor, 1996). The next section explores whether a simple combination of the Delphi-based and statistical forecasting methods leads to greater accuracy.

To do this the mean 'p' and 'q' values used in the Statistical method 2 (see section 6.4), were averaged with the 'p' and 'q' values of the most highly ranked analogies in the Delphi experiment. These averaged parameters were used to predict sales for target products. The analysis of the forecasting results is shown in the Table 1 below (the results for Statistical method 1 which used one best analogy is also shown again for comparison). Standard deviations and minimum and maximum values are also displayed to show the level of dispersion in the accuracy across the target products.

Table 13. Compare of the forecasting results

	Combined Stats method 2 and Delphi		Delphi using Best Analogy		Statistical method 2		Statistical method 1 (single analogy)	
	MdAPE	MMAPE	MdAPE	MMAPE	MdAPE	MMAPE	MdAPE	MMAPE
Mean	122.8	72.35	96.54	102.44	170.04	143.69	122.11	74.46
Median	67.95	66.28	73.85	53.86	48.82	54.30	66.22	66.28
Std. Deviation	259.13	46.09	148.46	159.09	399.31	288.86	313.04	64.49
Minimum	19.8	21.61	16.02	13.81	11.42	6.30	14.97	19.60
Maximum	1158.02	242.2	1002.71	759.86	1725.91	1248.70	2482.70	505.93

From the Table above it can be seen that the mean and median of the MdAPE and MMAPE did not improve as a result of using a combination of methods to select the analogies compared to the forecasting results, produced by the statistical methods 1 and 2 and by the involvement of Delphi method.

7. 4. Summary

In summary, there was no evidence that the participants in the Delphi study were able to identify which analogies were the most appropriate to use in new product forecasting. This may have been because the participants lacked expertise relating to the products, though the literature review suggested that expertise is not necessary for accurate forecasts. Alternatively, the information provided to the participants may not have been directly relevant to the selection of the best analogies.

Moreover, combining the judgment-based (Delphi) method with the statistical methods did not lead to improved accuracy. Armstrong and Collopy (1998) outlined conditions, which underline successful forecasting by integrating methods. They suggest that: a) domain knowledge has to be available to make judgments in choosing analogous sales trends; b) judgment has to be performed in a structured way; c) the judgments and statistical forecasts need to be independent, which can be achieved by careful structuring of the procedures used for integration, such as using a weighted integration approach. The authors (Armstrong and Collopy, 1998) listed previous works Makridakis et al. (1982), Bretschneider et al. (1989), Lobo and Nair (1990), Blattberg and Hoch (1990) which obtained improved accuracy in forecasting by means of the combination of the forecasts.

In the case of this research, the participants did not have specific domain knowledge, and that could be one of the reasons why the averaging approach did not produce improved results. Also, rather than combining actual sales forecasts it was the diffusion parameters that were combined and averaged in this research. These may the reasons of why the results in this research did not reveal better accuracy.

Chapter 8 Does using analogies adaptively improve forecast accuracy?

The analysis so far has involved using the ‘p’ and ‘q’ values for a given analogy (or the mean ‘p’ and ‘q’ values of several analogies) to produce forecasts for the target products using the Bass model. The results we have seen so far may suffer from two problems. First, the underlying sales pattern for any analogy, even the best, is likely to be different from that of the target because of differences between the products and the markets where they are sold. This suggests the need for adaption of the parameters obtained for the analogy to take into account the differences between the analogy and the target product (e.g. see Lee et al, 2007). Second, it is clearly difficult to select appropriate analogies either judgmentally or statistically. Therefore, using a single analogy to produce forecasts is highly risky because the selection is likely to be a poor one. Choosing several analogies may enhance the chances of choosing best analogous products among the rest.

This suggests that an alternative approach of using a large database of potential analogies and building models to explain variations in their ‘p’ and ‘q’ values, based on the product attributes, may be of value. The models can then be used to predict the ‘p’ and ‘q’ values that should be used for the target products. This is the forecasting approach that will be considered next.

8.1 Formulating the models

Stepwise regression was applied to the analogous products in order to obtain models to predict ‘p’ and ‘q’. This involved regressing the ‘p’ and ‘q’ values on to the nine characteristics identified in section 6.5.1 (e.g. the threat of a substitute product at the year of launch and whether or not the product is portable etc.) and four other variables: the estimated market saturation levels (m) for the product, the estimated number of days that a person on average income would have to work to buy the product in its year of launch and also four years after its launch and the logarithm of the number of observations available on the product’s sales. The last variable was used because Van den Bulte and Lilien (2001) have shown that ‘p’ and ‘q’ tend to be estimated too highly when relatively few observations are available and non-linear least squares is being used to fit the model. Logarithms of the number of observations were used because they (Van den Bulte and Lilien, 2001) also found that the relationship between the number of observations and the biases in the ‘p’ and ‘q’ estimates were logarithmic. Hence differences between the estimated ‘optimum’ ‘p’ and ‘q’ values of the analogies and targets may partly result from differences in the numbers of observations used to make these estimates. The first nine characteristics in the models were represented as dummy variables where a value of 1 indicated that the characteristic was present.

8.2 Obtaining the models and applying them to the forecasting task

After applying the stepwise regression for ‘p’ and the above independent variables, the following simple model was obtained:

p = 0.0209 - 0.00000002 m

Predictor	Coef	SE Coef	T	P
Constant	0.020863	0.002247	9.28	0.000
M	-0.00000002	0.00000000	-4.08	0.001

S = 0.00801322   R-Sq = 44.2%   R-Sq(adj) = 41.6%

The other independent variables were dropped by the analysis having a statistically non-significant influence on the dependent variable. Thus, only the market potential ‘m’ appeared in the final model.

The regression coefficient was significant at (p = 0.001) and R-squared was 44.2%

For ‘q’ the model selected by the stepwise regression is shown below. The p-values for the regression coefficients were: Usefulness, 0.076, Use to small businesses, 0.051, log of the number of observations, 0.000 and estimated saturation level (m), 0.005. The model had an R-squared value of 71.3%.

q = 1.064 - 0.09693 Usefulness - 0.11734 Useful to small bus - 0.28562 log no_obs
+ 0.00000022 m

```
Predictor                  Coef     SE Coef      T      P  VIF
Constant                 1.0640      0.1227   8.67  0.000
Usefulness             -0.09693     0.05155  -1.88  0.076  1.3
Useful to small bus    -0.11734     0.05608  -2.09  0.051  1.2
log no_obs             -0.28562     0.05038  -5.67  0.000  1.5
m*                   0.00000022  0.00000007   3.22  0.005  1.4


S = 0.106522   R-Sq = 71.3%   R-Sq(adj) = 65.0%
```

These models were used to predict the ‘p’ and ‘q’ values for the target products. These predicted values were then substituted into Bass models to forecast the sales of the targets. The results are shown below.

Table 14. Results of using analogies adaptively

	MdAPE	MMAPE
Mean	102.76	59.55
Median	57.02	53.02

8.3. Comparing the statistical and judgmental methods and their integration.

The accuracy of all the methods examined is shown in the tables below. (Recall that the Delphi method and the combined method were only applied to a subset of products).

Table 15. Statistical and judgmental methods, MdAPEs

	Stats method 1	Stats method 2	Delphi	Combined Stats method 2 & Delphi	Adaptive analogies
Mean	122.11	170.04	96.54	122.8	102.76
Median	66.22	48.82	73.85	67.95	57.02
Std. Deviation	313.04	399.31	148.46	259.13	225.82
Minimum	14.97	11.42	16.02	19.8	5.6
Maximum	2482.7	1725.91	1002.71	1158.02	1074.03

Table 16. Statistical and judgmental methods, MMAPEs

	Stats method 1	Stats method 2	Delphi	Combined Stats method 2 & Delphi	Adaptive analogies
Mean	74.46	143.69	70.83	72.35	59.55
Median	66.28	54.3	69.83	66.28	53.02
Std. Deviation	64.49	288.86	159.09	46.09	51.39
Minimum	19.6	6.3	13.81	21.61	8.9
Maximum	505.93	1248.7	759.86	242.2	261.62

Friedman's rank test was used to compare the accuracy of all of the forecasting methods as well as their combination. Friedman's non-parametric test was used because the error measures did not have a normal distribution. The following steps have been followed:

The variables compared were the MdAPEs and MMAPEs, obtained by

1) Statistical methods, described earlier, where one best analogy was chosen (Statistics method 1)
2) Statistical methods, described earlier, where best three analogous products were chosen and the Bass model parameters averaged to obtain a final forecast (Statistics method 2)
3) Involvement of judgment (via the Delphi method) to identify analogous products
4) Combining judgmental and statistical approaches, discussed earlier

5) The adaptive analogies method (discussed in the first part of this chapter).

The analysis revealed that there was no statistically significant difference between these methods on either accuracy measure. It also showed that an integrated approach produced results close to those, obtained by a statistical approach (Method 1).

However, the adaptive analogies method has the lowest mean and median MMAPE and the lowest mean and Median MdAPEs (when the Delphi method which was performed on a subset of products is excluded). Importantly, adapted analogies also had the lowest standard deviation on both measures (again excluding Delphi in the case of the MdAPE) suggesting that the method carries less risk because its results are more consistent than the other methods across a range of different products.

How did the accuracy of the methods compare to the benchmarks that were discussed in section 6.2? The figures below show compare the results for the median MdAPE and median MMAPEs (the five benchmarks are shown on the left of the graphs)

Figure 8 All results compare, MdAPEs

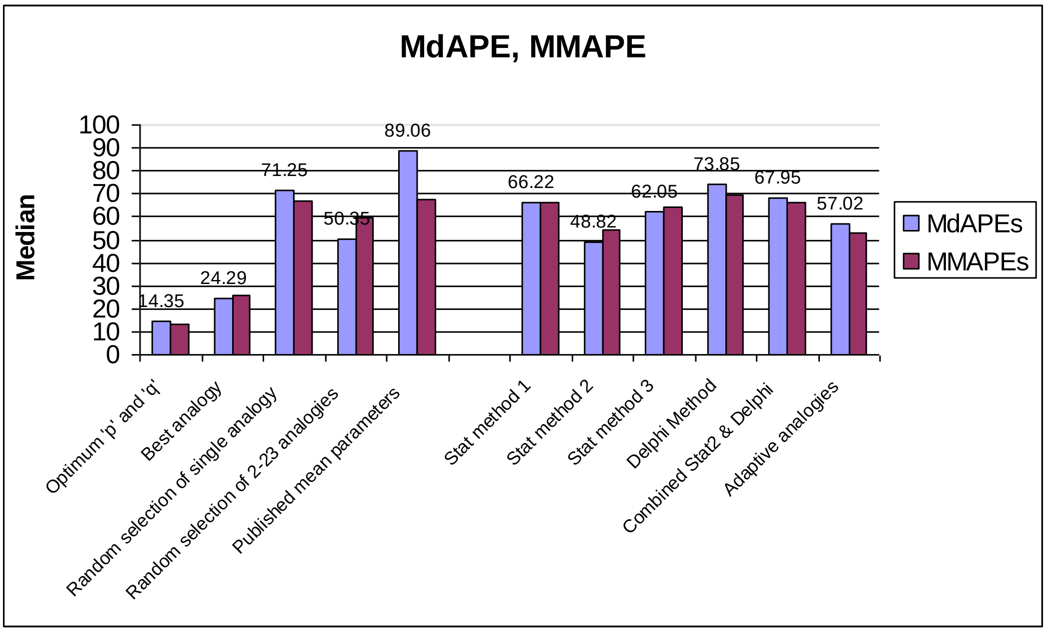
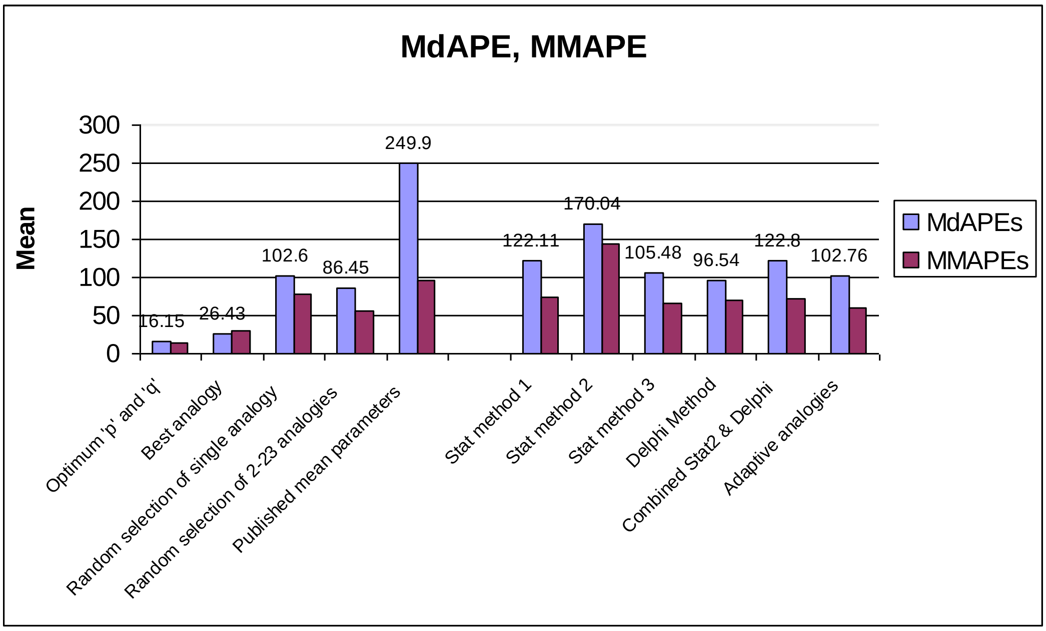


Figure 9 All results compare, MMAPEs



The most important result here is that there is little to choose between simply using the mean 'p' and 'q' of the all analogies in the database and adaptive analogies when the median of the MdAPEs and MMAPEs are used to measure overall performance.

8.4 Summary

Overall these results show that the use of analogies in order to identify appropriate 'p' and 'q' values for a target product could not achieve median MMAPEs of below about 53% and median MdAPEs of below about 50%. The relatively high values reflect the difficulty of the forecasting task that was attempted here. These difficulties will be explored further in the final chapter.

If lower forecast errors in the early years of a product's life are more important than errors in later years this will be reflected by the MdAPE. On this measure the most advisable strategy would be to use mean 'p' and 'q' values of all the analogies since this method offers the benefits of simplicity, in addition to yielding the most accurate forecasts, on average. Also this research suggests that externally published parameter values or the random selection of analogies should be avoided.

If forecasting accuracy is equally important across the entire life of a product then the MMAPE will be a more appropriate measure of accuracy. On this measure there is much less to choose between the methods, though again the random section of single analogies and the use of published parameter values are not advisable. In this case the choice from the remaining methods should probably be based on other criteria like cost, simplicity and the time required to produce the forecasts.

Chapter 9 Conclusions and suggestions for further work

9.1 Introduction

This research addresses a vitally important topic for businesses, namely the forecasting of the sales of new products before their launch on the market. It, for the first time to the knowledge of a researcher, explicitly addresses the problem of practitioners in finding a most valid model in new product forecasting and performs empirical comparison of the main three approaches in forecasting: statistical, judgmental and their combination.

High errors are to be expected in new product forecasting. The absence of past data and the fact that the forecasts are made for many years ahead in markets which are likely to be dynamic, if not turbulent, mean that the task is a challenging one. In this thesis we attempted to compensate partly for the absence of past data by using data on analogous products, but sizeable errors were still observed.

In this final chapter the source of these errors will be explored and it will be argued that the task that was examined was probably more challenging that that which applies in many company forecasting environments. On that basis, it was argued that further work in evaluating some of the techniques that were presented here at company level may well be worth pursuing. The limitations of the research are also discussed and the extent to which they restrict the extent to which inferences can be drawn from the thesis for new product forecasting in practice will also be assessed.

9.2 Main findings

The aim of this research was to determine a new product forecasting model, which would produce accurate forecasts and be simple enough for ordinary managers, who are not sophisticated in statistical modelling, to use in practice.

Practical evidence show that although statistical approaches to forecasting have a number of advantages, such as objectivity in the estimations, less time required for performing a forecast, little cost and no need for the application of extensive domain knowledge, managers still prefer judgmental approaches in forecasting future trends. The main reason for this seems to be no clear understanding of which statistical model to choose in given situations and a lack of skill in using those statistical instruments. Therefore, individual and panel judgments are widely used for predicting future sales.

This research aimed to compare a relatively simple and accurate statistical model with a relatively simple and accurate method of using judgment for forecasting. Also, since many researchers noted (as discussed in the literature review) that combining several forecasting methods should provide better accuracy, an integration of those methods was also explored. The results were compared in the attempt to draw conclusions about an approach that could be recommended for new product forecasting.

The results revealed, however, that there was no statistically significant difference between either of those approaches. Nevertheless, an individual scrutiny of the error indices suggests that the increase in the number of analogies used for the target product forecasting, yields higher accuracy. For example, using three analogies in the statistical method resulted in the lower median MdAPE and in a further MdAPE decrease when all analogies were used. Therefore, it leads to a conclusion that in the statistical forecasting approach, as much analogous products' sales data as possible should be used in order to enhance accuracy.

Although the evaluation of the products' structuring variables to identify analogies did not lead to an improvement in results that was statistically significantly, there was still some evidence of accuracy improvement. This suggests that future research into the use of the structuring features of analogous products is worth considering.

Average MdAPEs and MMAPEs indicate that Delphi method performed best among those three approaches (statistical, judgmental and the combination of them), followed by a statistical approach. However, although comparison between different judgmental methods was not performed, this being outside the scope of this research, managers should pay considerable attention in choosing the method that is most likely to allow the exclusion of judgmental bias to the maximum extent. Previous research has suggested that the Delphi method meets this condition. All of the approaches, however, produced more consistent and somewhat better results than those of previous studies in this area (e.g. the work of Lilien et al., 1999).

9.3 Discussions of the results

1. Does the statistical identification of analogies based on product characteristics lead to more accurate forecasts than: a) using industry average parameter values and b) using randomly selected analogies?

This research has focused on the problem of forecasting future time series values of products which have yet to be launched. It has tested empirically the existing methods of forecasting future time series of sales data for target products to be launched that have no previous sales history. For that, sales data of analogous products were used in order to identify the diffusion model parameters.

The primary demerit on the use of analogies as a way of forecasting is the simple fact that it is significantly under researched. There is very little literature available on the new product forecasting on the basis of analogous products' data. Also very few studies have compared existing methods of forecasting new products. This research aimed to make a contribution by filling the existing gap in this area.

This section considers the first research question (as stated above) and attempts to establish various circumstances under which statistically identified analogies yield higher forecasting accuracy.

The results revealed that the difference between the methods was not statistically significant. However, a closer look shows that when the median of the individual products' MdAPEs and MMAPEs were calculated the statistical identification of analogies, based on such product characteristics as 'the date of launch', pricing, advertising and 'the number of days to work to purchase a product' (a substitute for a price), led to more accurate forecasts than using industry average parameters (published) and randomly selected analogies. Averaging parameters of three products, selected statistically and structurally (using product characteristics), also produced better results than using 2 to 23 product parameters, selected randomly.

When the mean of the individual MdAPEs and MMAPEs were calculated this showed however that using parameters of randomly selected 2-23 products led to more accurate results than when single analogies were chosen on the basis of their attributes. This may mean that choosing a product randomly consistently provided 'averaged' results, where median and mean of errors did not differ too much; while in the case of choosing analogies by a structural approach, results were distorted by some extreme values, which resulted in much higher mean error values than the median.

Overall it is obvious that using more analogies improved accuracy, which can be explained by the fact of 'averaging out' the errors when more analogies were used to identify the diffusion process parameters. This finding supports the earlier discovery of Thomas (1985), who advised using 3-5 analogous products in order to enhance accuracy. This research suggests that in case of high uncertainty, the more products used in the analysis the better results are expected to be. Although a structured approach is recommended (error medians are still lower than those of randomly chosen products), pooling together all available product data may serve as a substitute.

The results also demonstrated that identifying analogies structurally is better recommended than using readily available (published) industry parameters. This may be explained by the variations in the environments where forecasts are performed and using product data from the same environment (industry, country) leading to accuracy improvement.

This research also performed a formal procedure to test if more product traits would add value to the accuracy improvement in the sense of identifying best analogies. This involved three researchers (who are experts in the area):

1. Each of them independently identified a set of key characteristics that were thought to link the analogies to the targets.

2. The researchers then met to identify (at length) common factors and to discuss whether factors that differed between the three of us should be included.

   The identified factors were used to identify the best analogies. A comparison of the error measures suggests that the results improved accuracy, although again, the differences were not statistically significant.

This approach had the advantage of a formal structure which allowed the researchers to exercise their independent judgment at the initial stage of the process. There was still a danger that important product underlying factors would be missed but the use of three independent judges and subsequent discussion was designed to reduce this risk. The opposite danger of identifying irrelevant factors would have been identified when linear regression analysis was applied to the factors (assuming that the factors did not interact). This suggests that future research could usefully investigate the effectiveness of using this approach with a larger group of experts.

Using the Bass diffusion model.

Next, the question arises whether using the Bass diffusion model for sales forecasting of new products is a valid approach and whether different results (higher accuracy) could be achieved if an alternative method had been applied instead.

As was discussed earlier in the literature review, the Bass model is not free from limitations. For example, rich sales data of analogous products are required (up to the product maturity stage) and it does not include external variables explicitly, which may distort the adoption process. Also, it is assumed that the diffusion parameters are stable over time. Further, in many practical situations it may be difficult to find a sufficient number of analogous products with sales data up to the maturity stage to reliably estimate the Bass model parameters. However, alternative growth curve models such as Gompertz and logisitic curves would also suffer from these limitations and they would not have the advantage of providing managers with a transparent rationale to explain diffusion patterns; while the use of management judgment to produce the forecasts would likely suffer from the many biases that were discussed in the literature review.

When a few data points of sales on a product are available some of these problems are reduced. For example, Decker and Gnibba-Yukawa (2010) considered including a function of a hazard rate of a diffusion process, which is equal to the conditional purchase probability of a product. This can be established by analysing the early stages of a product adoption. However, this approach would not meet the main objective of this research which was to find a parsimonious and simple statistical model for *new* product forecasting. Indeed, the Decker and Gnibba-Yukawa model includes several components and hence requires more data to be collected in order to construct a model. However, this approach may be recommended for future research which is designed to explore situations where more complex models are likely to be accepted by managers. This is also true of stochastic models, which allow the dynamics of the diffusion parameters to be captured. One such model was developed by Putsis (1998). He considered the income level as a key variable to be taken into account in diffusion models and developed a model that incorporates replacement sales and marketing – mix variables. The model contains the Bass model as a special case.

In summary, the Bass model still remains one of the most practical options for forecasters to obtain new product forecasts in a cheap, simple and quick way.

2. Do human judges, participating in the Delphi method, select more appropriate analogies than statistical methods?

There was no statistically significant difference between the accuracy of the forecasts produced by these methods, but a detailed consideration of the results still provides some evidence that the Delphi method led to more accurate forecasts. Previous research has revealed that companies prefer judgmental forecasting to statistical methods for new product forecasting (Klassen and Flores, 2001; Landetta, 2006 McCarthy et al., 2006). However, others have stressed that a structured approach is always preferable to unaided judgment (Fildes et al., 1978, Armstrong, 1985, Kahn, 2006). This research therefore applied a highly structured approach to the elicitation of judgments. This may have played a role in the higher accuracy achieved by the Delphi method compared to the statistical approach (although not statistically significant). Other methods for obtaining judgments from groups would therefore have been expected to be less effective than Delphi. For example, interaction groups or panel discussions of analogies might have led to results that over-emphasised the views of dominant personalities or led to self censorship by individuals who perceived that their views lacked conformity with the rest of the group. The Delphi method is also easier to organise and less time consuming than these alternatives. The first of these advantages is achieved by conferring anonymity on the panellists which allows each member to put forward his or her opinion confidentially without fear of victimisation or ridicule (Kahn, 2006; Rowe and Wright, 1999; Linstone and Turoff, 1975). This is likely to reduce emotional stress bias, where some people can be stressed by the necessity to express their opinion in front of a group through fear of being judged. Emotional stress can have an impact on the psychological disposition that will affect the participant's ability to make accurate judgments. Social pressure bias has a huge impact on human judgment, when a majority of people or some dominant people in the group may significantly influence the judgments of other group participants and damage the quality of the survey (Kahneman and Tversky, 1979). Hence, anonymity and autonomy reduces group pressure (Armstrong, 2006). Rowe (1998) noted that in a group discussion, while some individuals may dominate the conversation, less confident participants tend to keep silent, therefore the group opinion becomes polarised around the opinions of the stronger-spirited participants.

Delphi was designed to improve judgmental quality compared to traditional groups by adding structure to the process and evidence suggests (Sniezek, 1990; Erfmeyer and Lane, 1984; Riggs, 1983) that Delphi groups are more accurate than traditional groups in pooled discussions. Rowe and Wright (1999) found in a review of the related literature that Delphi groups outperformed unstructured groups by a score of five studies to one and should be preferred to other judgmental methods in forecasting.

In general, there is a scarcity of research into how well the performance of judgmental approaches compares with that of statistical methods in new product forecasting and one of the very few studies exploring this was carried out by Astebro and Koehler (2007). Their general assertion, based on previous studies was that statistical forecasting instruments are far superior to judgmental methods - only experts' forecasts, made in a highly structured way, can give results comparable to statistical methods. The reason is that experts are not able to decode predictive cues in available information unless they are highly experienced. The authors examined experts' forecasts of the commercial potential of new products. They were given a large set of sales data and asked to use their judgment to predict future sales. They found that intuitive judgment is inevitably exposed to bias and tends to distort the forecasts, resulting in wrong predictions. In order to avoid such bias, the authors proposed a highly structured, systematic way of forecasting, and achieved about 80% correctness in predicting cases. The same data set was also used to make predictions by means of a statistical tool - an optimal linear statistical prediction model, and a 98% forecasting accuracy was achieved, which is still higher than obtained by the judgmental method.

The Delphi technique itself has undergone several studies in the quest to determine its validity and reliability. For example, Dalkey et al., (1970), Brockhoff (1975) Rohrbaugh (1979) and Dietz (1978) found Delphi to be better than statistical methods or at least had no statistically significant difference in accuracy from statistical methods (see also Ono and Wedermeyer, 1994). Other studies have found similar results (Fisher, 1981; Sniezek, 1990).

This research showed no statistically significant difference with the statistical method at the 95% confidence level, which can be considered as a high achievement on behalf of the Delphi method, given a high degree of uncertainty inherent to the task and the variety of analogous products to choose from to forecast sales for target products.

Last but not least is the question of whether using experts in the Delphi study rather than novices would have yielded significantly better results. Rowe and Wright (1999) have carried out a review of research into the Delphi method and found that there is slight evidence that using experts in the panel does matter. However, they also refer to the works of Welty (1974) and Armstrong (1985), who suggested that expertise is of little value for forecasting tasks due to the high uncertainty inherent in the task.

In particular, it may be a tricky task to identify expertise in identifying analogous products. There is certainly a lack of people specially trained and having great industrial experience in finding similarities in analogies, therefore the matter of identifying expertise in this domain becomes problematical. Experts in high technology industries, which may be defined as those who have practice and experience in the domain, still need structure in their judgment and may not necessarily outperform people with general knowledge in understanding the differences and similarities between sales patterns in TV sets and Radio recorders. This problem of how expertise can be defined has been highlighted in the literature on cognitive psychology. It was stressed in particular that "In some domains, professional licensing has sufficed as a criterion for the identification of experts". (Hoffman, 1996: 82).

The problem of disagreements among experts has also been addressed, and the question was asked "If the "experts" are experts, why do they disagree? And since they do disagree, how can one rely on their judgments in setting policy?" (Hoffman, 1996: 83). In the case of identifying analogies uncertainty is high and there would likely be disagreements among "experts" as well, so how can we rely on their judgments? In addition, like non-experts, their judgments suffer from such phenomena of cognition, as memory limitations and reasoning biases.

A number of studies in cognitive psychology (Adelson, 1984; Phelps and Shanteau 1978; Spiro et al. 1989) also suggest that "experts" with practice lose the qualities of being conscious, making effort and deliberating (in contrast to novices) and their judgments become "intuitions", which is associated with experience and restricted to automatic pattern recognition rather than a deliberative analysis of deeper structure.

The distinction between experts and novices in this research case becomes even harder since even for an experienced person in a high technology industry or an academic with years of experience in forecasting or decision making, identifying analogies is likely to be as much of a new task as for a business student or a professional with experience in other domains. Greeno (1978) and Scribner (1984) found that while experts may be good in recognising patterns from their past experience, they are just ordinary people in reasoning and problem solving.

In the case of sales forecasting it has been found that novices can predict as accurately as experts (Welty, 1972; Armstrong, 2001; Green and Armstrong, 2006).

Armstrong (2001) and Green and Armstrong (2006), found that experts' accuracy in prediction is usually little better than the forecast accuracy of novices. One of the reasons they mentioned, was that experts tend to be more confident in their estimations and do not explore the possibility of inaccuracy in their predictions. Similarly, Tetlock (2005) demonstrated, in a large study involving 82361 political and economic forecasts that experts performed worse than chance. However, they also demonstrated fine abilities to justify and defend their mistakes. While people are likely to believe experts, their advantage in forecasting in many domains is no more than an illusion and it is therefore difficult to assert that experts are better than lay people in terms of ability to make better predictions. Forecasting ability may be simply narrowed down to an ability to use the accompanying information effectively. Although experts may still have advantages in knowing how certain dynamics will affect sales patterns, their overconfidence in their judgements may prevent them from objective analysis and considering other factors, which may also have crucial impacts on sales. Novices, on the other hand, being less confident, may consider all conditions and factors when they make their forecasts.

Finally, much literature suggests that in Delphi there are advantages in having panels made up of members with heterogeneous expertise (Schiano et al., 1989; Rowe and Wright, 1999; Donohoe and Needham, 2009). The dispersed expertise helps to reduce bias and errors in individual judgments, deriving from misunderstandings or incomplete knowledge by combining opinions (Sewart, 2001). The research described in this thesis brought together, in the Delphi panel, people with various backgrounds, such as MBA and PhD students, professionals in various domains, including sales and forecasting and academics. Therefore, the integrated judgments should have had a high probability of yielding the best possible judgments, given the information that was available.

Therefore, it may be concluded that the results, obtained through empirical studies in this research, are valid and provide reliable estimates of the power of the judgmental method, in this case – the Delphi method, against a statistical method in new product sales forecasting.

3. Does the combination of 'purely' statistical forecasts and forecasts based on the judgmental selection of analogies lead to improved forecast accuracy?

The research results revealed no statistically significant difference in accuracy between either of the three methods tested: statistical, judgmental and the combination of them, however a closer look at the combination of methods worked well, producing better than the worst and worse than the best results. Since means and medians show somewhat opposite results in terms of best and worst methods (statistical or judgmental identification of analogous products), the combination of the methods always took a middle position between them and may be recommended at times of high uncertainty, where it is uncertain which method would produce better results.

Different forecasters may have a difficult time in the identification of the particular conditions necessary for the situation they wish to forecast. This brings out a need for the use of different methods based on the conditions that are assumed in any particular situation. Once such forecast made the two to be combined through predetermined rules of the forecast. This combination of such forecasts (statistical forecast and judgmental forecast) goes a long way in improving the accuracy by bringing down the error margin of a forecast. By questioning, one may be able to view the great benefit that accrues from the combination of statistical forecasts and judgmental forecast.

The probability and extent of the reduction of the error value of the forecast is highly increased when the forecast methods are increasingly varied (Batchelor and Dua, 1995). Citing an example from the GNP (Gross National Product) forecast on the United Kingdom (Batchelor and Dua, 1995), the use of a combination of same methods of forecasts yielded a 11% reduction in the error value, while forecasts performed by varied methods were combined and resulted in a 23% reduction in the error value of the forecast. Much care should be taken especially with the use of differential weight. They are only to be used in instances where there is solid evidence of very accurate forecasts.

In a meta- analysis of about 30 studies of combination of forecasts up to a 12% decrease in the error value in all the instances was achieved in comparison to the average error of the particular components. This clearly depicts that the combined forecasts are most of the times recommended to increase accuracy (Armstrong, 2001). In citing another example in the combination of the housing prices forecast from about 6 different methods it was found that the error margin decreased by 1-2%, which is a more modest change (Chen et. Al., 2009).

Further studies from the meta-analysis studies revealed that under good favorable conditions the error level can be reduced by almost half (Graefe et al., 2010). Therefore, the combination of forecast aids the forecaster to evade large errors that he may make. Especially in the case when a forecaster is highly unsure of the accuracy level achieved by individual forecasting methods. It has been greatly acknowledged that the error level can significantly reduce even though the forecasts were done by the same individual (Herzog and Hertwig 2009).

Overall it is logical that the combination of the methods did not lead to a statistically significant improvement in the accuracy since the combined methods (statistical and judgmental) did not differ significantly in accuracy from each other; therefore we can follow a slight improvement, which is consistent with earlier findings that a combination does lead to improvement in forecasting and the conclusion is that the higher the variance in accuracy, the more significant accuracy improvement can be achieved through their combination.

9.4 Why the specific forecasting task investigated was challenging

The task of forecasting annual sales in the USA of new consumer electronics products using the sales data in the Consumer Electronic Association (CEA)'s data base was probably more challenging than the task encountered in many individual companies for several reasons.

First, the products used in this research were very diverse. They included portable headsets HDTVs, fax machines, projection equipment, car satellite navigation equipment and mobile phones. In most companies it is likely that there would be many more products that were similar to a given target product so that 'better' analogies might be expected. The modelling approach might be more successful in producing accurate sales forecasts when earlier versions of a given product (or brand) are used to forecast later versions of the same product (rather than using one product's sales to forecast sales of a completely different product).

Second, the time differences between the launch dates of the products were often extensive. The analogies had a mean launch date of 1979 while the mean launch date for the targets was 2000. The potential analogy in the data base with the earliest launch date was monochrome TV which was first marketed in 1946. The most recently launched target product, digital projection sets, was first sold in 2004. Clearly, there will have been huge changes in the markets for electronic products over these years. But have these changes affected the typical values of the coefficient of innovation (p) and the coefficient of imitation (p)? To investigate this the estimate ‘p’ and ‘q’ values for all the products were examined and these are shown in the graphs below.

Figure 10 All products p-estimates

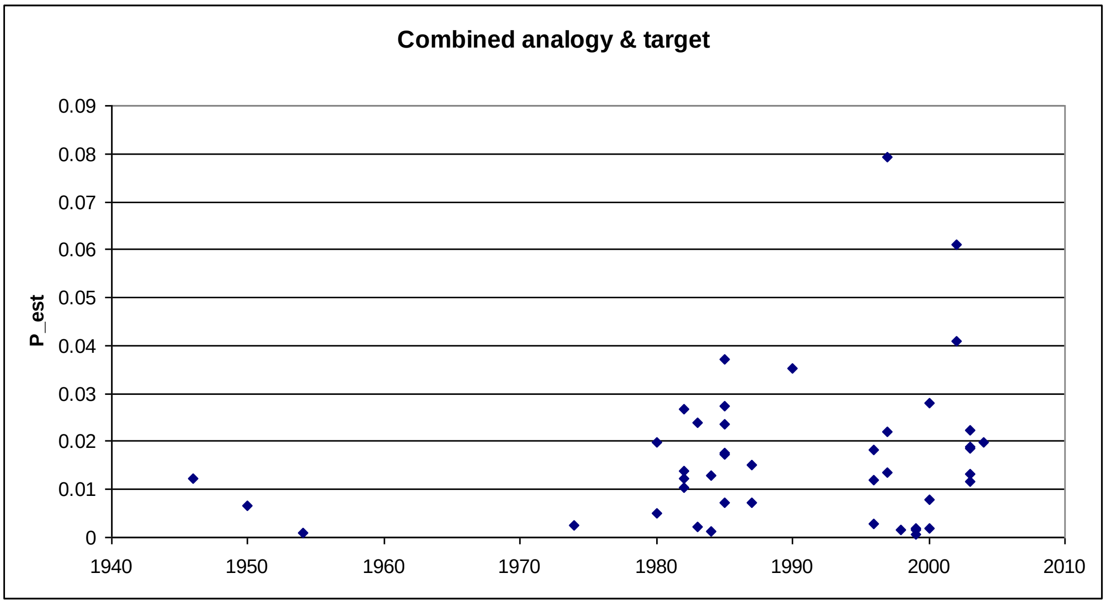
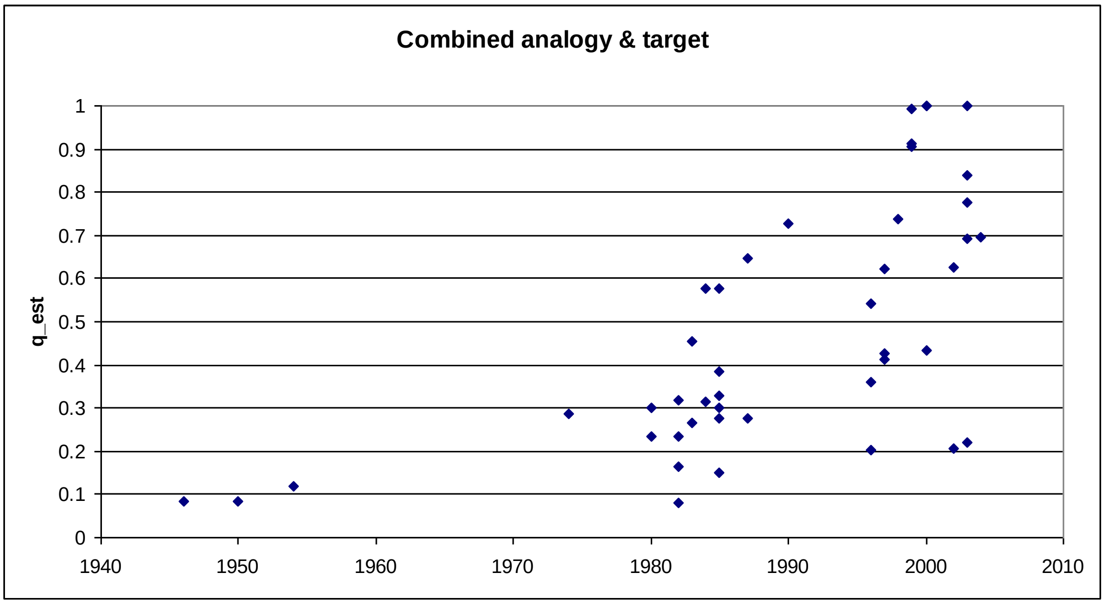


Figure 11 All products q-estimates



It can be seen that for ‘q’, in particular, there has apparently been a general rise in both its mean value and its variation between the pre-1995 launched products (the analogies) and the post-1995 products (the targets). This will clearly limit the potential accuracy of forecasts based on the ‘p’ and ‘q’ values of the pre-1995 products.

However, these apparent differences may be misleading. When the Bass models were fitted to the sales of the analogies up to 1995, the number of available observations was usually greater than the number available for the targets. The mean number of observations available for the former was 15.9 and, for the later, it was 10.0. It is possible that the differences are simply a result of the number of observations used in the estimation. Recall that Van den Bulte and Lilien (2001) have shown that ‘p’ and ‘q’ tend to be estimated too highly when relatively few observations are available and non-linear least squares is being used to fit the model. However, analysis carried out by Goodwin (2011) indicates that the values of both p and q have increased even after the different number of observations have been taken into account (Goodwin, 2011).

This may suggest that a substantial increase in q has occurred between the pre- and post-1995 products and for some reason; imitation appears to be having a stronger effect on people’s tendency to purchase new electronics products. This may be because the electronic product market competition became more intense and consumers developed practical savvy in choosing electronic products, which would create value of money, so the opinions of those, who already purchased the product started having greater influence on the purchase decision-making.

This research addressed the problem of using analogous products and the availability of them, given that for the Bass diffusion model, products with life cycles up to the maturity stage is preferable to use, there may be not many analogous products available and big gaps in the years of launch are possible therefore. This research demonstrated that using analogous products, especially with scattered years of launch along decades is not easy and leads to the results in the accuracy level, found here.

However, differences between launch dates as large as this would unlikely to apply to most companies making forecasts for their new products. This will particularly be the case in markets where state-of-the-art products are rapidly updated and improved. However, in these circumstances the problem would be different in one important respect to the problem addressed in this thesis: sales of potential analogies over incomplete product life cycles would need to be used to forecast sales of target products which will also be likely to have incomplete life cycles.

9.5 Limitations of the research

Inevitably, this research has a number of limitations. The most obvious is that the simple Bass model was used here. This was designed primarily to forecast diffusion, but it was used here to forecast sales. A more elaborate sales forecasting model would have required components which took into account of additional purchases by consumers and also replacement purchases. No data was available to support estimation of the first component. An attempt was made, early on this research to include a component representing replacement purchases, assuming that the time between replacements followed probability distributions like the symmetrical triangular or Poisson distributions. This modelling was not successful given the scarcity of the available data. However, the inclusion of these more complex components would have violated one of the key objectives of this research anyway which was to find a relatively simple procedure for managers to forecasts sales of new products.

This consideration also partly accounts for the second simplification of the Bass models, namely the omission of marketing mix data. An absence of detailed marketing mix data was a second reason for this omission. However, arguably this data is accounted for to some extent by the coefficient of innovation (p), as was explained in the literature review section 2.3. Moreover, where such data was available (e.g. on the price of the product) it was used in the forecasts of p and q in the adaptive analogies procedure (Chapter 8). Of course, a further limitation is the assumption that the Bass parameters remain constant throughout a product's life.

Another limitation relating to the Bass models was the assumption that the saturation level, m, was known as the time of the product's launch. The accuracy of the methods described in this thesis may be less than those reported if it is not possible to achieve accurate estimates of 'm' by means such as product intentions surveys or demographic data.

In addition, research by Chandrasekaran and Tellis (2007) showed that the Bass parameters estimations suffer from bias.. This was also noted in earlier research (Van den Bulte and Lilien, 1997), that the market potential tends to be underestimated by around 20% and the coefficient of innovation can be overestimated by 30 %.

Finally, it was also found in earlier research that the model parameters fluctuate with the addition of new observations (Golder and Tellis, 1998; Heeler and Hustad, 1980; Van den Bulte and Lilien, 1997). Further "noise" in the forecasts produced by this model may happen due to the uncertainty in the diffusion process, especially around the inflection point and the saturation level (Franses, 2005). The cumulative number of adopters may not be described by an ideally smooth curve (Franses, 2005), caused by individual-specific effects on the hazard rates or caused by the influence of external factors. However, Golder and Tellis (1998) argued that this limitation is mitigated by the ability of the quadratic function to fit sales well enough to estimate the true underlying behaviour of the product adoption.

The exploration of the effectiveness of using judgment to identify appropriate analogies also had a number of limitations. Hence, it was not possible to obtain a rich database of objective (i.e. statistical) contextual information relating to the products. This constraint will have restricted the capability of the human judges to adjust to identify appropriate analogies.

Another of the limitations in this research is that data is limited to the electronic industry. In the light of resource constraints, a convenience sampling procedure was applied (data were obtained from available and accessible sources), and therefore just one industry – electronics – was investigated. Because of this it may not be possible to draw inferences from these results for other industries. For example every industry has its own specific characteristics and the attributes which make some products suitable analogies for others is likely to vary. High technology products, for example, are known as having a high level of consumer involvement in purchase decisions and high technology products tend to have a higher diversification in order to justify higher prices at the initial stage of the product introduction due to high R&D costs (Gardner et al., 2000). Therefore it may be more difficult to find analogies among the products. Those products also tend to have differentiated utility levels for consumers; therefore it also creates difficulties in identifying analogies easily. In contrast, low technology products are described by lower prices, low consumer involvement in purchase decisions, and therefore consumers tend to be influenced more easily by emotionally appealing advertisements, which, for example, emphasise the taste of sweetness and indulgency in advertising ice cream. This may make it easier to find analogies between products (e.g. ice cream vs. cakes and biscuits).

Patterns of product diffusion will also differ. For example, low technology products face rapid growth or a rapid decline rate, their product life cycle is longer than that of high technology products, and high technology products have a greater degree of turbulence at the earlier stage of the product life cycle (Riggs, 1983).

All this makes it difficult to generalise results across the industries. However, quality of data is also as important as the sample size (Grey, 2004). For example, for one product to forecast on a base of analogous products, three or four analogous products need to be identified in order to find a best analogy, and thus achieve the most accurate forecasting. Moreover, the analogous product must have a sales history starting much earlier than the new product. Therefore, the availability of high quality data for the electronics industry, which corresponded to those requirements, gave an opportunity to perform a deeper analysis.

The inclusion of data on products from the 1940s in the database on analogies may also be perceived to be a limitation, given changes in consumer preferences and economic conditions since this time. However, most other studies in this area have included much older data, For example Lilien et al (1999) included a series going back to 1815. Moreover, many of the methods discussed in this thesis were designed to automatically filter out inappropriate analogies (e.g the nearest neighbour analysis based on the Gower similarity coefficient) or reduce their impact (e.g. the regression analysis). Hence, if using older product data was inappropriate, these methods would have excluded them.

Another possible limitation of the research arose because only 6 products were offered to the Delphi panel to choose from for a target product, while it would be ideal to provide all 23 analogous products to choose from and rank them in similarity to the target product.

However, the argument is that providing all possible analogies for the target product would not enhance the reliability of the forecasts due to the inability of people to deal with large amounts of data (Stewart, 2001). As discussed earlier in the literature review, judgments are influenced by various sources of bias and in this case such types as *complexity bias* would distort the judgments significantly. This bias arises when too much information places a cognitive burden on human memory and may have a detrimental effect on prediction accuracy. Along with this information overload, time pressure and distractions lead to a decrease in consistency of judgement. Also, when dealing with a large volume of information, people tend to simplify the task by using the '*best guess strategy'*. This bias comes from simplification by ignoring the uncertainties and relying on the "most likely" scenario. When the uncertainty is high it is very difficult to predict outcomes and people may tend to stick to the "most likely scenario", based on analogous or stereotypical cases. These simplifications would also involve relying on just one or two attributes to assess the similarity between an analogy and a target product, while a multi-attributed assessment might be required.

And finally, the *bias resulting from habit* would significantly hamper the results, as people tend to choose 'habitual' alternatives. Therefore, among those 23 products, it would be highly likely that people would choose the best analogy based on the recent memory of using either of those products rather than scrupulously estimating each of them. Given the above listed bias sources and inability to assess a large amount of data, the validity of the results would be seriously damaged.

9.6 Suggestions for further work

All of this suggests that there are a number of avenues that could usefully be pursued in future work.

1. The ideas could also be tested on other products in other industries, countries and markets

2. The ideas tested here could be applied to individual new products in companies. As indicated earlier it seems likely that more accurate forecasts would be obtained in this environment.

3. Bass models that formally incorporate marketing mix variables and a component for the replacement of products by consumers would also be worth testing to see whether the use of analogies here would improve forecast accuracy, given that more parameters would have to be estimated from the analogies.

4. It may be worth extending the work of Decker and Gnibba-Yakawa (2010) and focus on forecasting the first fewer data points of sales series, rather than data up to the maturity stage. Indeed the early sales of new products are likely to be of most interest to managers as they face decisions on whether to continue to market them.

5. More sophisticated models of diffusion models are worth consider ding. These include not only marketing mix variables explicitly but also variables relating to phenomena such as democratisation of innovation (Decker and Gnibba-Yakawa, 2010) (price dropping after some time of the new product launch), network effects (direct network effects: the product improvement along the generations of the product and indirect network effects: which occur as the range of complementary products increases (e.g. DVDs for a DVD player), and forward – looking behaviour (where consumers wait until the quality of the product improves and the price drops). The relative accuracy of these more sophisticate models can also be compared to judgmental approaches.

6. Given the finding that the parameter, q, has increased over time it would be worth exploring the use of trend-based forecasting models to see if values of q suggested by the analogies can be adapted to take into account to take into account this upward trend. As such it may also be worth trying to explore stochastic models, which capture the dynamics of the diffusion parameters rather than assuming that their values remain constant

7. Given the difficulty of finding the closest analogous products in order to achieve higher accuracy in forecasting, based on analogies, further research could usefully focus on additional features of products, which may help to identify analogies, based on their deeper structures.

Also, a bigger number of panellists is worth investigating in order to reproduce the formal procedure of identifying those features which was carried out in this research.

In the application of the Delphi method it would be worth assessing the value of employing experts rather than lay people. For this it may also be worth exploring how easy it is to find relevant experts within companies and how well they perform compared to novices or MBA and PhD students in the relevant domain in identifying analogies and/or performing new product forecasting.

8. Further work on the Delphi method may prove to be fruitful. This would take into the account all the current weaknesses of the procedure and the possibilities of eliminating them.

9. Finally, the focus of this research was on consumer electronics products. There is a huge need for research into sales forecasting for new fast moving consumer goods. Many for the methods developed here could usefully be tested on these products.

9.7 Final word

In summary, forecasters and researchers routinely suggest the use of analogies when the Bass model is to be applied to new product forecasting. Before the work was carried out for this thesis this recommendation appears to have been largely untested and based purely on presumption and speculation. This thesis has shown that the identification and use of analogies is neither trivial nor easy and that it is by no means guaranteed to produce reliable forecasts. Given the prominence of the Bass model in the forecasting literature and also given that new product forecasting is the key role of the Bass model, this is finding has potentially important implications for both research and practice.

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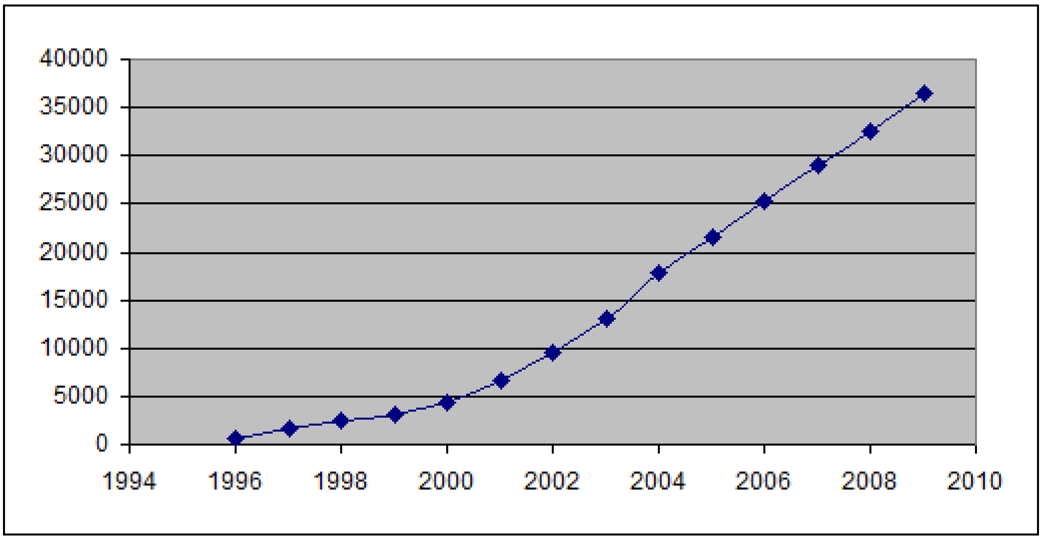
APPENDICES

Appendix 1. Target products sales data

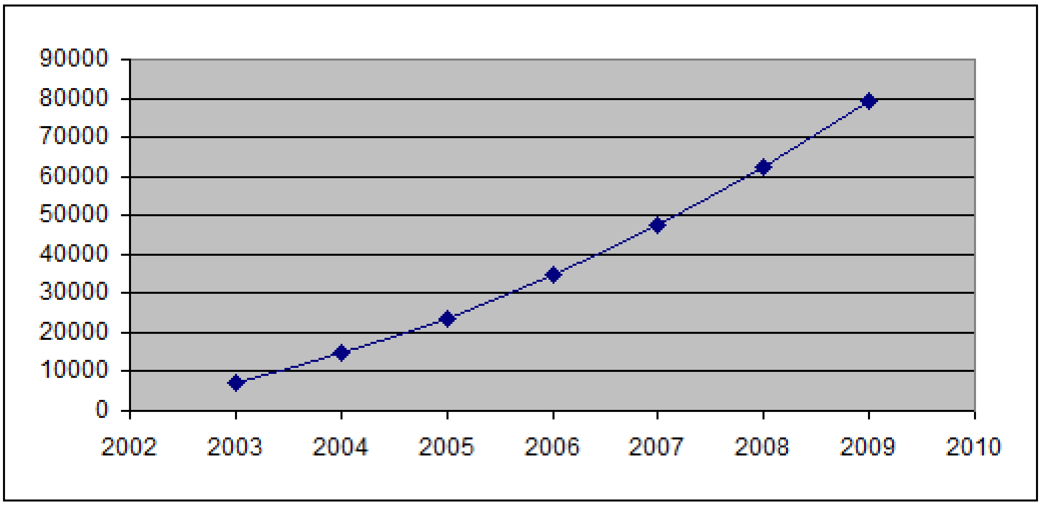
Home Theater-in-a-Box

Year	Actual	Cumulative
1996	621	621
1997	979	1600
1998	784	2384
1999	806	3190
2000	1157	4347
2001	2304	6651
2002	2793	9444
2003	3622	13066
2004	4702	17768
2005	3807	21575
2006	3679	25254
2007	3722	28976
2008	3623	32599
2009	3963	36562



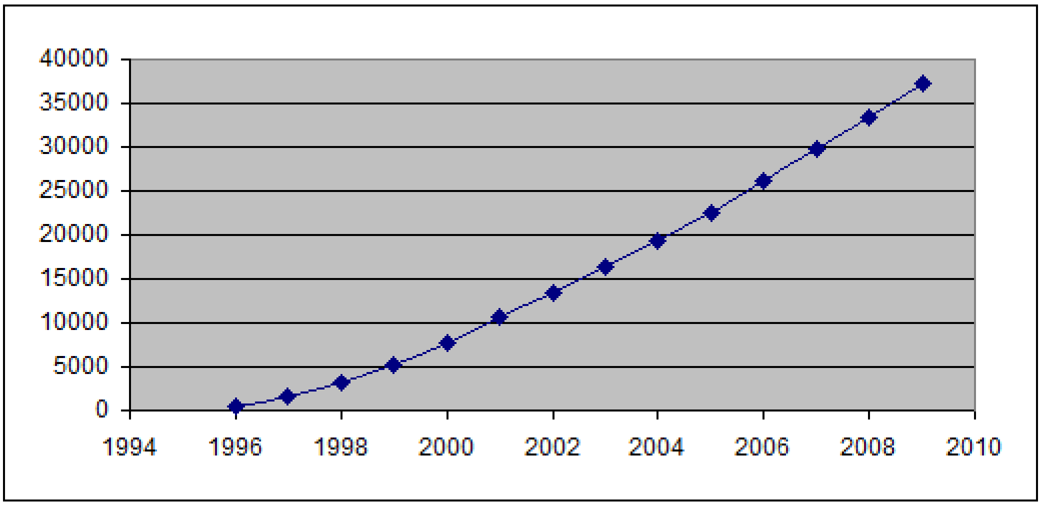
Cable/Multi-System Operator Receivers

Year	Actual	Cum
2003	7150	7150
2004	7750	14900
2005	8463	23363
2006	11208	34571
2007	13235	47806
2008	14780	62586
2009	16450	79036



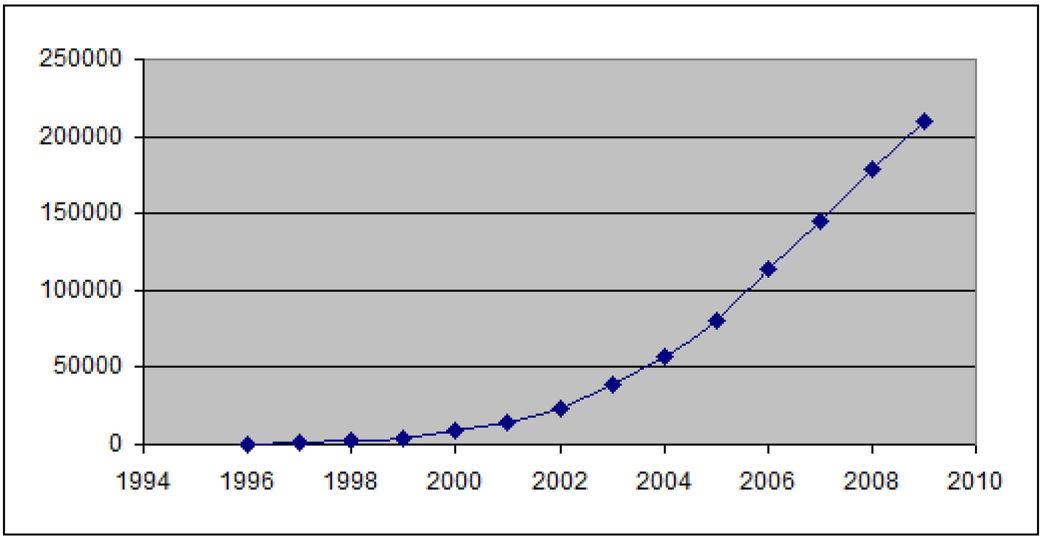
Caller ID Devices

Year	Actual	Cum
1996	517	517
1997	1169	1686
1998	1604	3290
1999	2044	5334
2000	2286	7620
2001	2962	10582
2002	2864	13446
2003	2815	16261
2004	3088	19349
2005	3209	22558
2006	3560	26118
2007	3634	29752
2008	3650	33402
2009	3829	37231



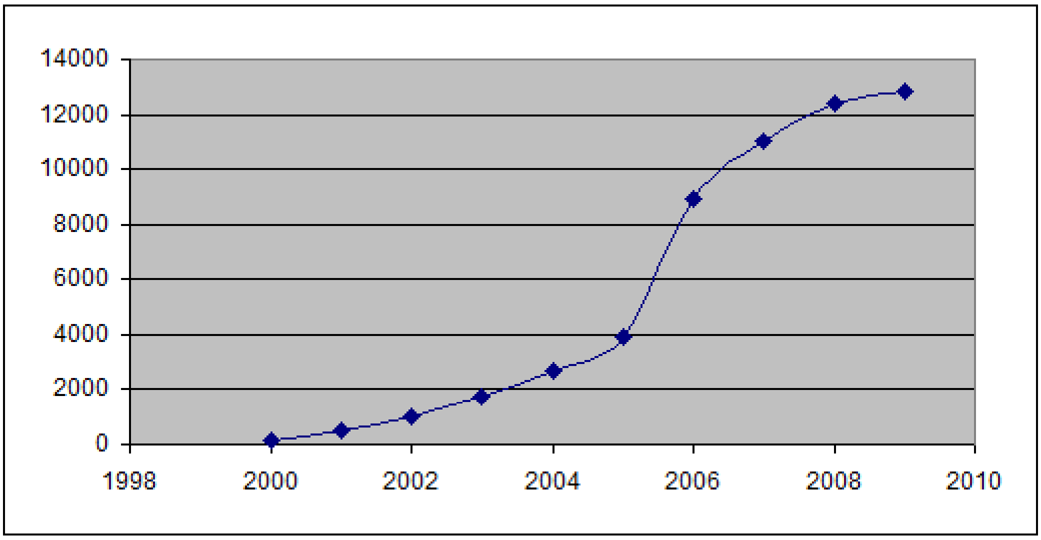
Digital cameras

Year	Actual	Cum
1996	300	300
1997	863	1163
1998	1180	2343
1999	2114	4457
2000	4234	8691
2001	5556	14247
2002	9267	23514
2003	14786	38300
2004	18852	57152
2005	23249	80401
2006	32947	113348
2007	32220	145568
2008	33168	178736
2009	31018	209754



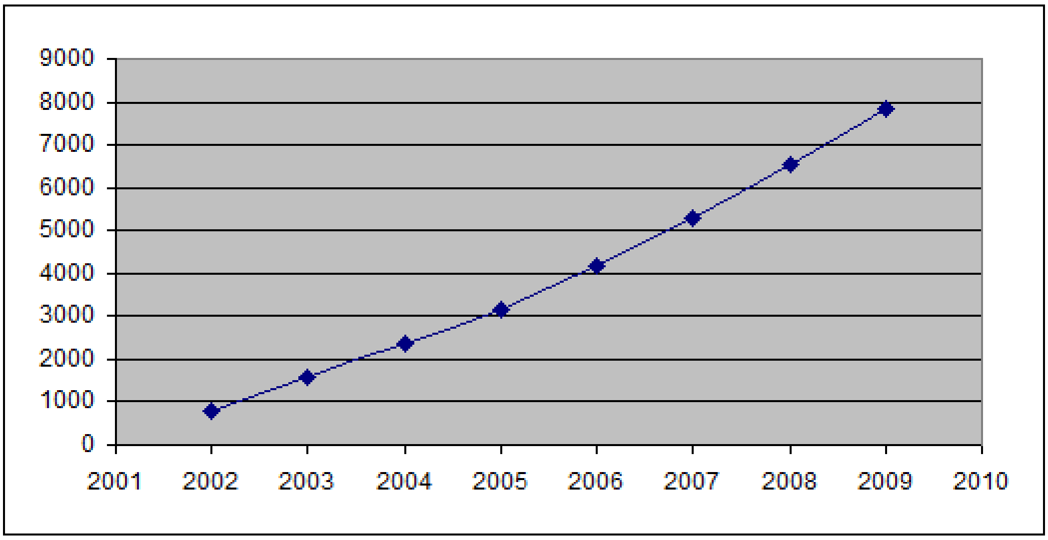
Digital Direct-View Sets & Monitors

Year	Actual	Cum
2000	148	148
2001	361	509
2002	530	1039
2003	703	1742
2004	974	2716
2005	1236	3952
2006	4946	8898
2007	2164	11062
2008	1324	12386
2009	476	12862



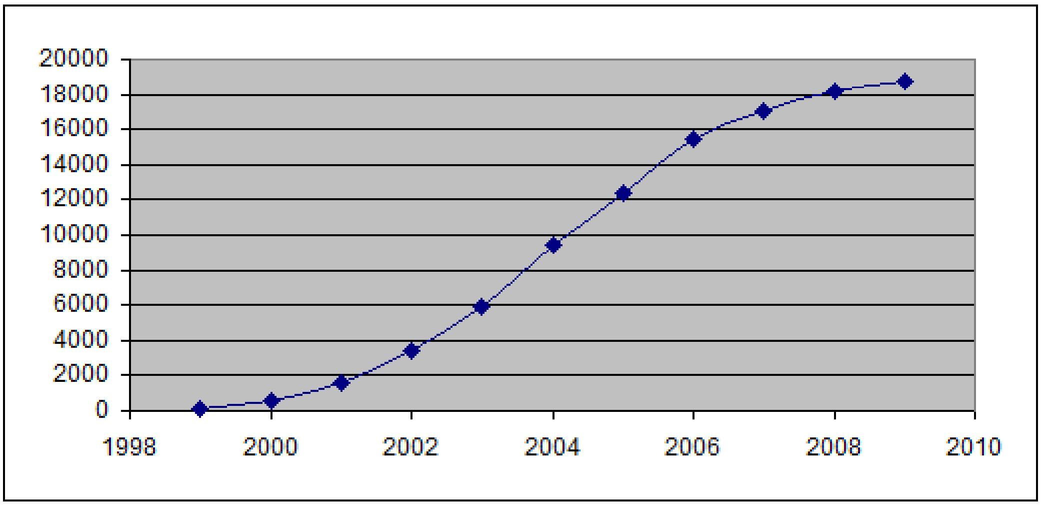
Digital Front Projection TV

Year	Actual	Cum
2002	770	770
2003	790	1560
2004	806	2366
2005	802	3168
2006	1003	4171
2007	1122	5293
2008	1240	6533
2009	1312	7845



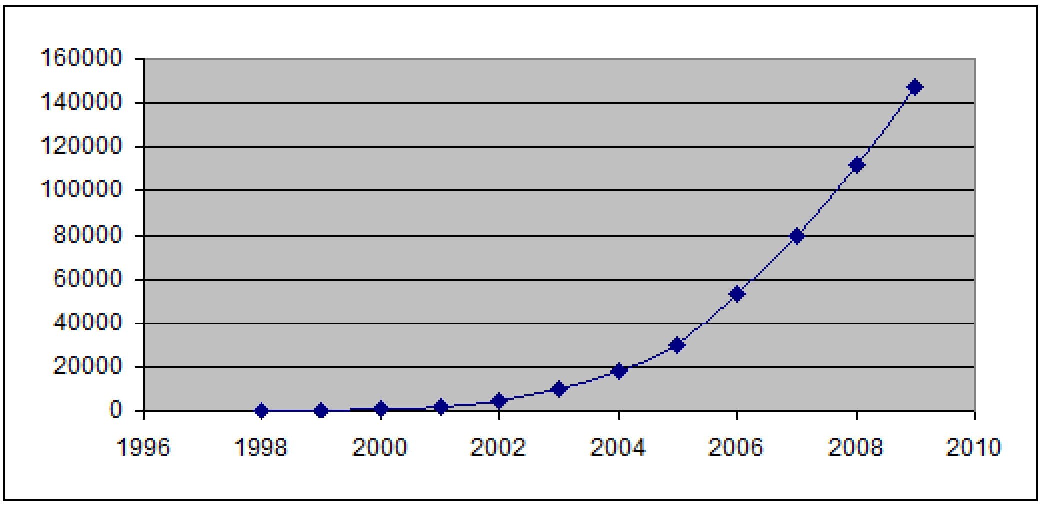
Digital Projections Sets & Monitors

Year	Actual	Cum
1999	100	100
2000	492	592
2001	1045	1637
2002	1804	3441
2003	2444	5885
2004	3510	9395
2005	2965	12360
2006	3064	15424
2007	1671	17095
2008	1070	18165
2009	628	18793



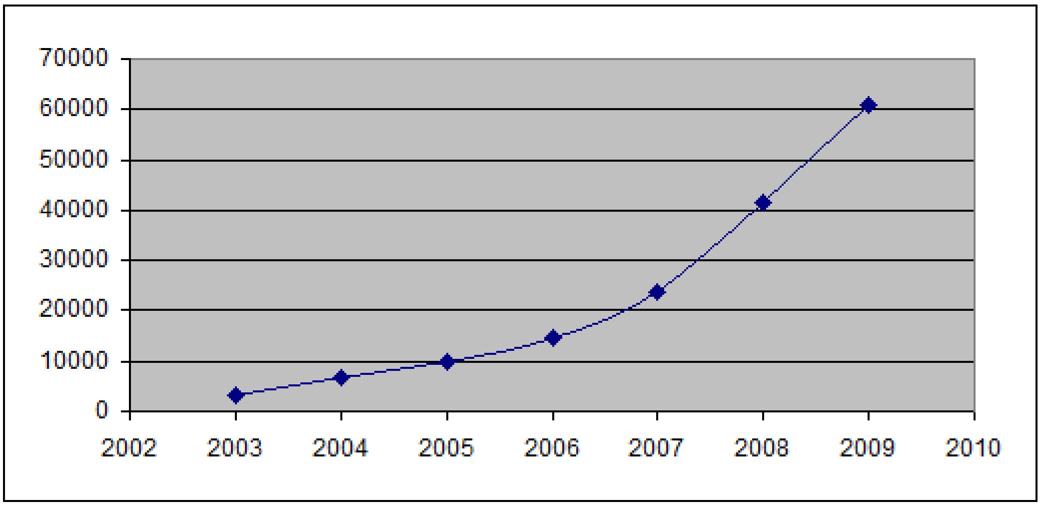
Digital TV Sets & Displays

Year	Actual	Cum
1998	14	14
1999	121	135
2000	625	760
2001	1460	2220
2002	2535	4755
2003	5532	10287
2004	8002	18289
2005	11369	29658
2006	23504	53162
2007	26409	79571
2008	32743	112314
2009	34639	146953



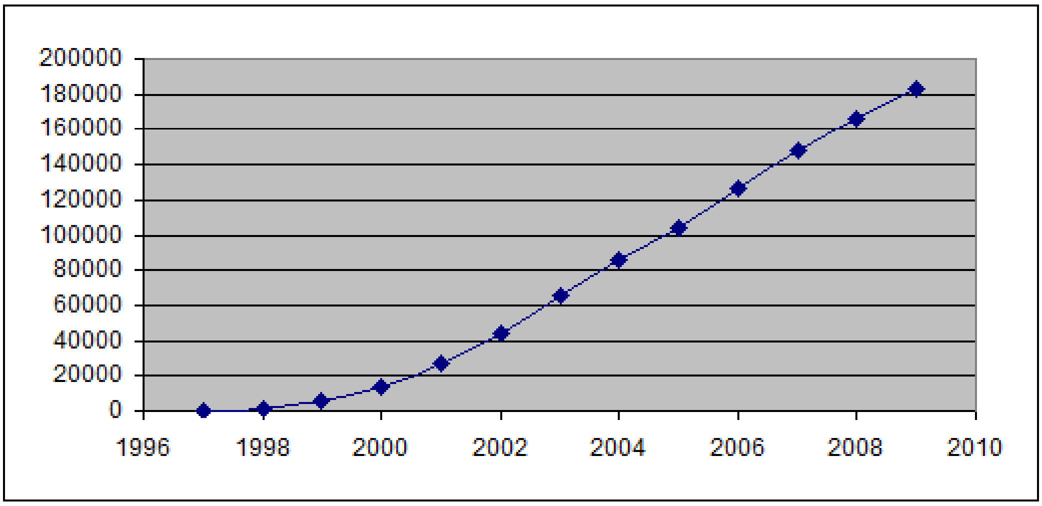
Digital VCRs

Year	Actual	Cum
2003	3255	3255
2004	3345	6600
2005	3174	9774
2006	4980	14754
2007	8912	23666
2008	18054	41720
2009	19004	60724



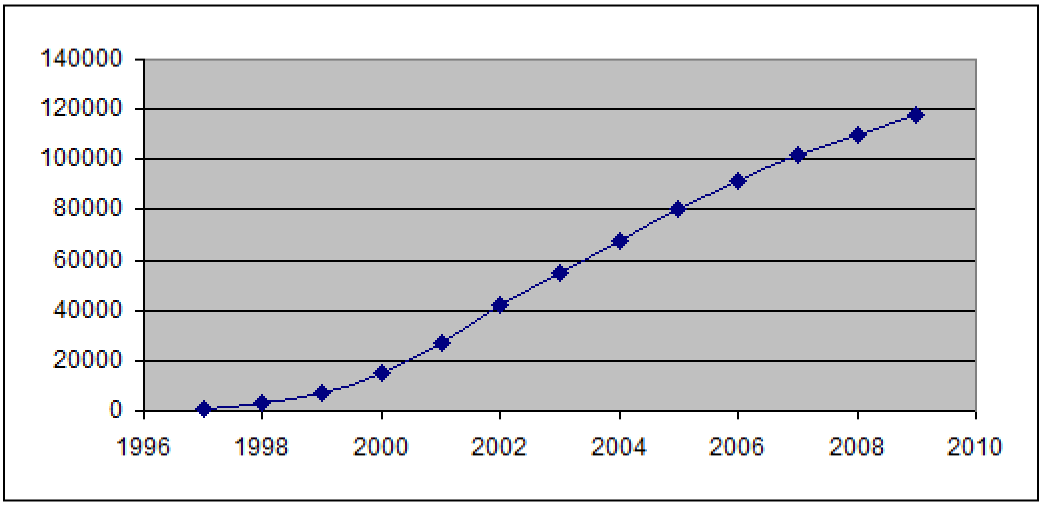
DVD Players/Recorders

Year	Actual	Cum
1997	349	349
1998	1079	1428
1999	4072	5500
2000	8499	13999
2001	12707	26706
2002	17090	43796
2003	21994	65790
2004	19990	85780
2005	18626	104406
2006	22306	126712
2007	20919	147631
2008	18969	166600
2009	16123	182723



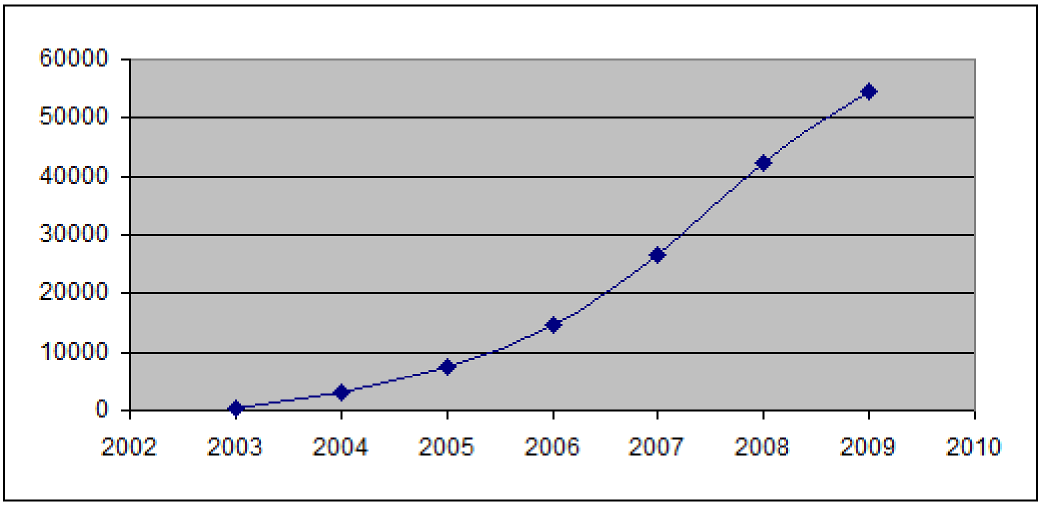
Family Radio Devices

Year	Actual	Cum
1997	500	500
1998	2500	3000
1999	4500	7500
2000	7300	14800
2001	11942	26742
2002	15382	42124
2003	12558	54682
2004	13060	67742
2005	12550	80292
2006	11295	91587
2007	10025	101612
2008	8354	109966
2009	7518	117484



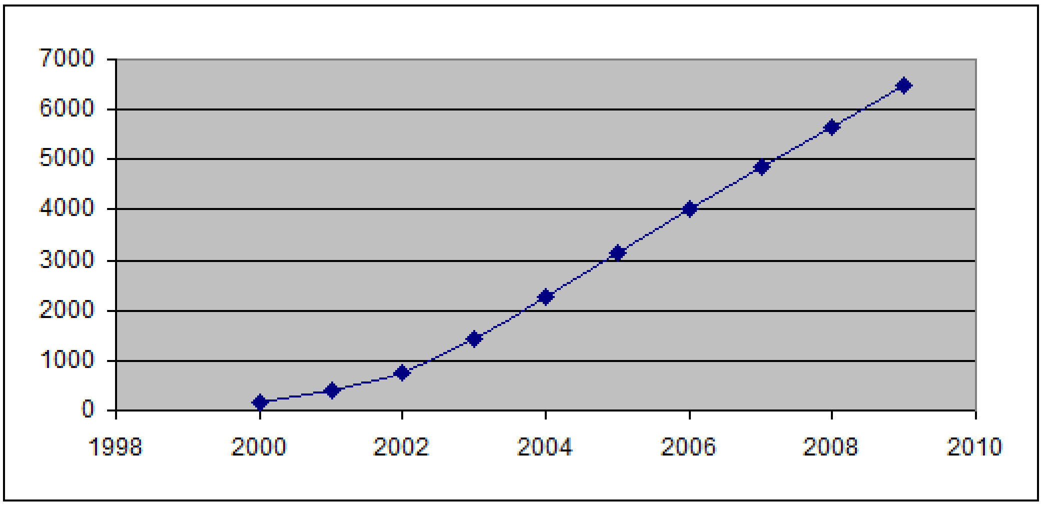
HDTV

Year	Actual	Cum
2003	500	500
2004	2500	3000
2005	4500	7500
2006	7300	14800
2007	11942	26742
2008	15382	42124
2009	12558	54682



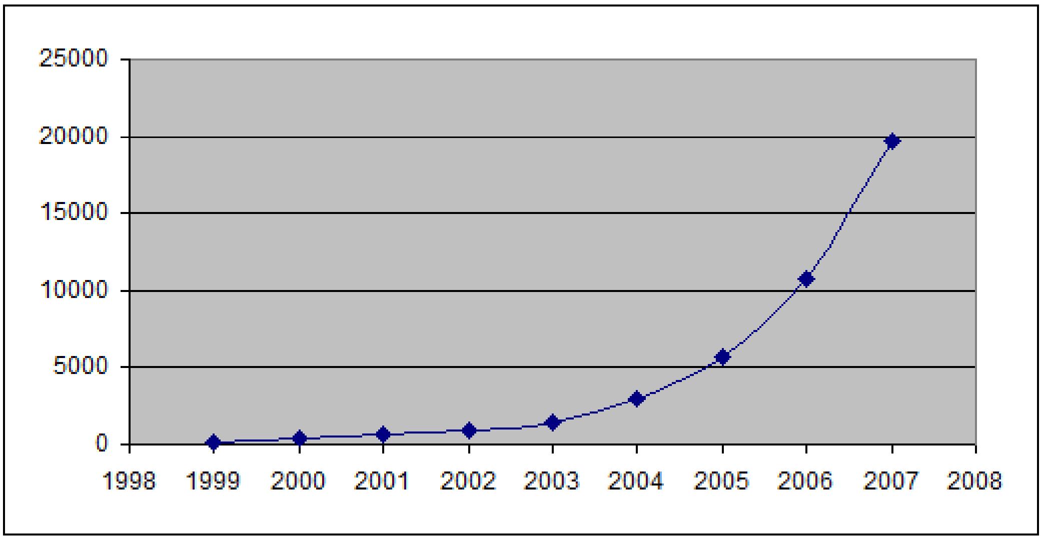
Personal Digital Assistants

Year	Actual	Cum
2000	150	150
2001	245	395
2002	350	745
2003	675	1420
2004	850	2270
2005	875	3145
2006	880	4025
2007	825	4850
2008	800	5650
2009	835	6485



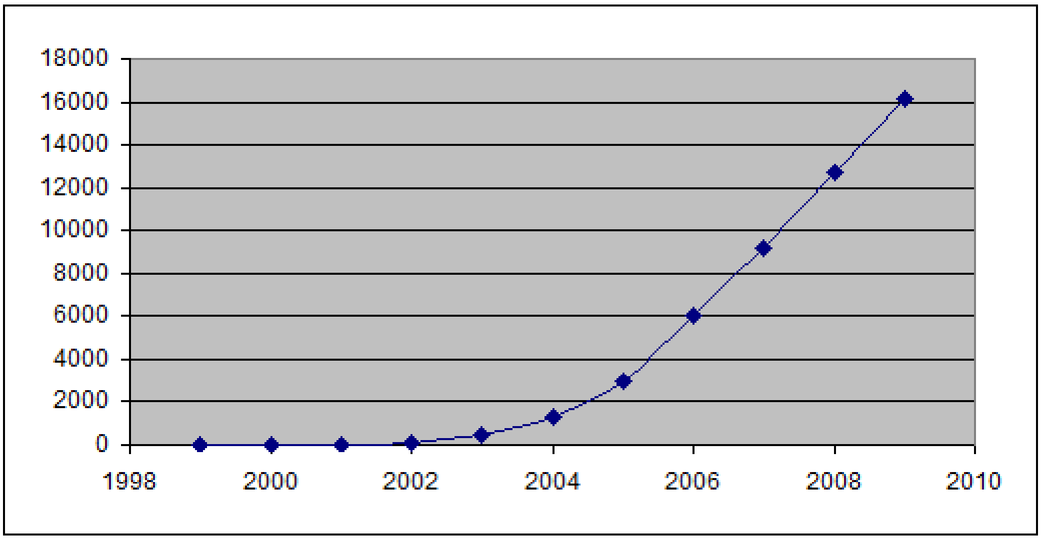
Personal VCR

Year	Actual	Cum
1999	100	100
2000	249	349
2001	336	685
2002	170	855
2003	519	1374
2004	1647	3021
2005	2727	5748
2006	4980	10728
2007	8912	19640



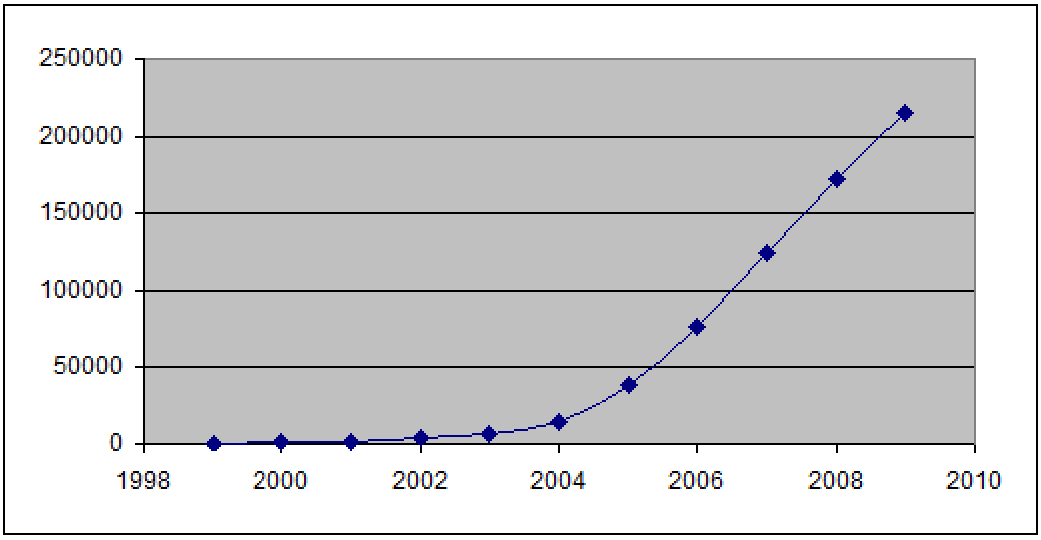
Plasma DTV

Year	Actual	Cum
1999	2	2
2000	8	10
2001	16	26
2002	106	132
2003	342	474
2004	870	1344
2005	1639	2983
2006	3028	6011
2007	3166	9177
2008	3572	12749
2009	3403	16152



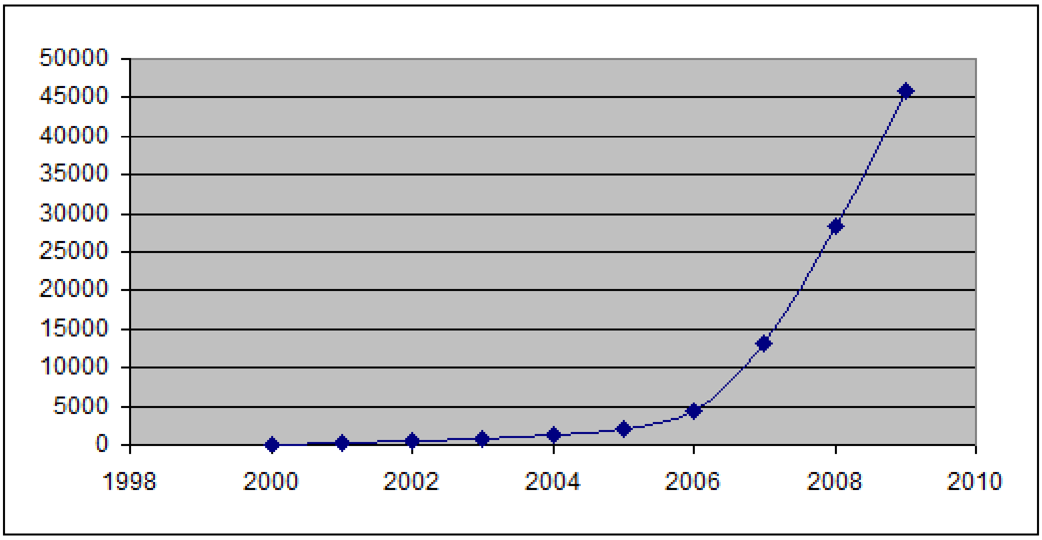
Portable MP3 Players

Year	Actual	Cum
1999	500	500
2000	587	1087
2001	724	1811
2002	1737	3548
2003	3031	6579
2004	7126	13705
2005	24812	38517
2006	38124	76641
2007	48020	124661
2008	47792	172453
2009	42091	214544



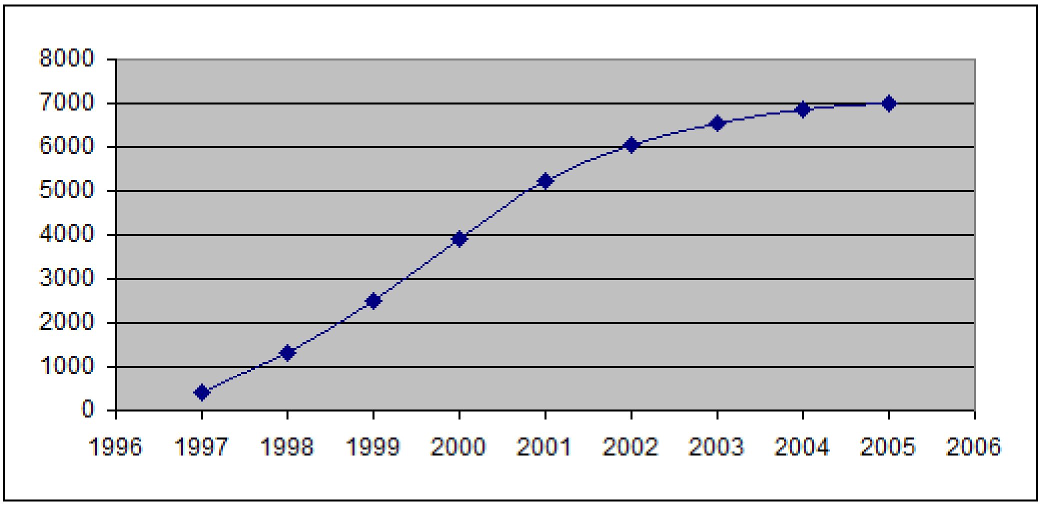
Portable and Transportable Navigation

Year	Actual	Cum
2000	107	107
2001	162	269
2002	221	490
2003	300	790
2004	550	1340
2005	707	2047
2006	2284	4331
2007	8751	13082
2008	15320	28402
2009	17410	45812



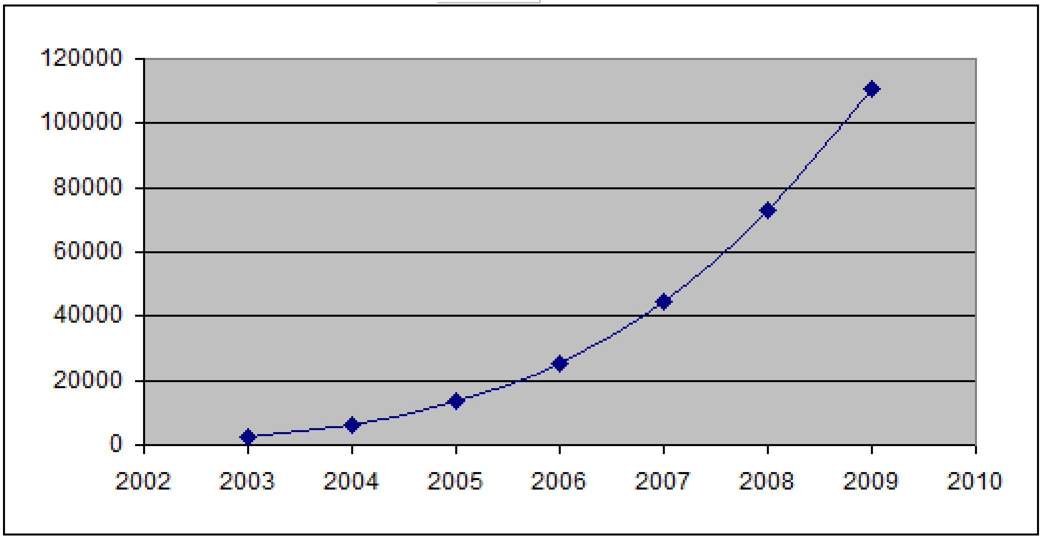
Set-top Internet Access Devices

Year	Actual	Cum
1997	400	400
1998	917	1317
1999	1200	2517
2000	1400	3917
2001	1300	5217
2002	850	6067
2003	500	6567
2004	285	6852
2005	150	7002



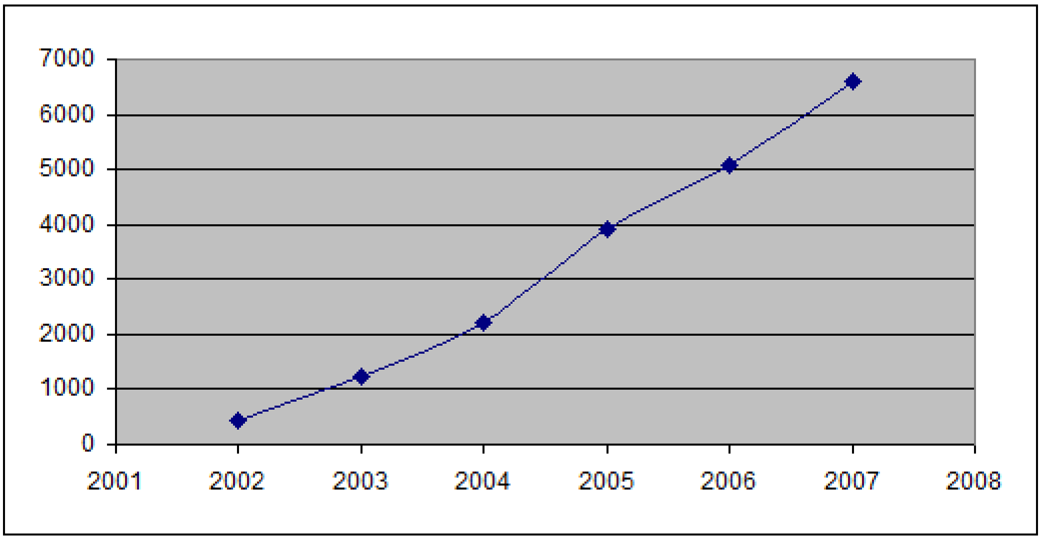
Smartphones

Year	Actual	Cum
2003	2306	2306
2004	3627	5933
2005	7920	13853
2006	11282	25135
2007	19500	44635
2008	28600	73235
2009	37400	110635



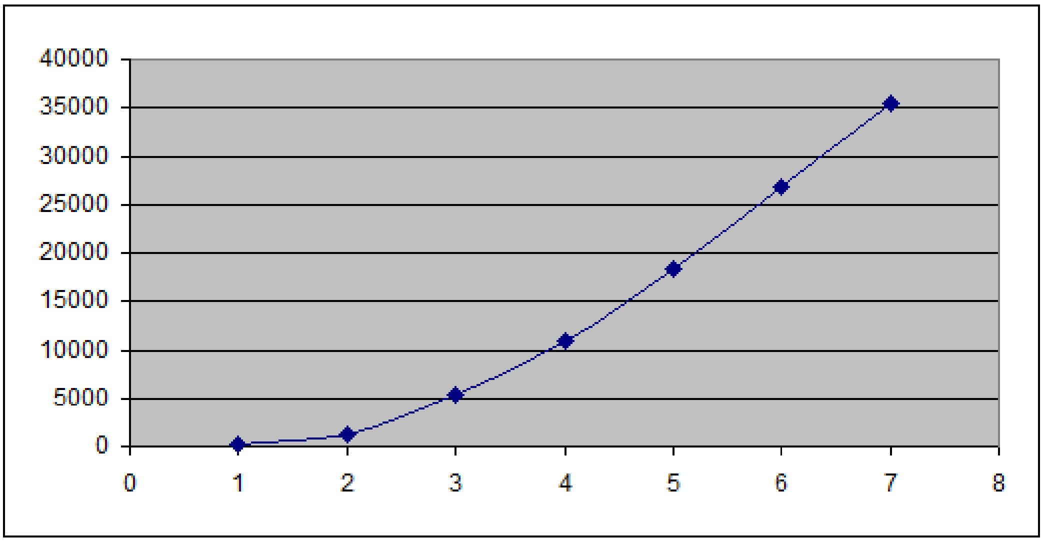
TV/DVD Combinations

Year	Actual	Cum
2002	450	450
2003	793	1243
2004	979	2222
2005	1710	3932
2006	1138	5070
2007	1536	6606



VOIP Adapters

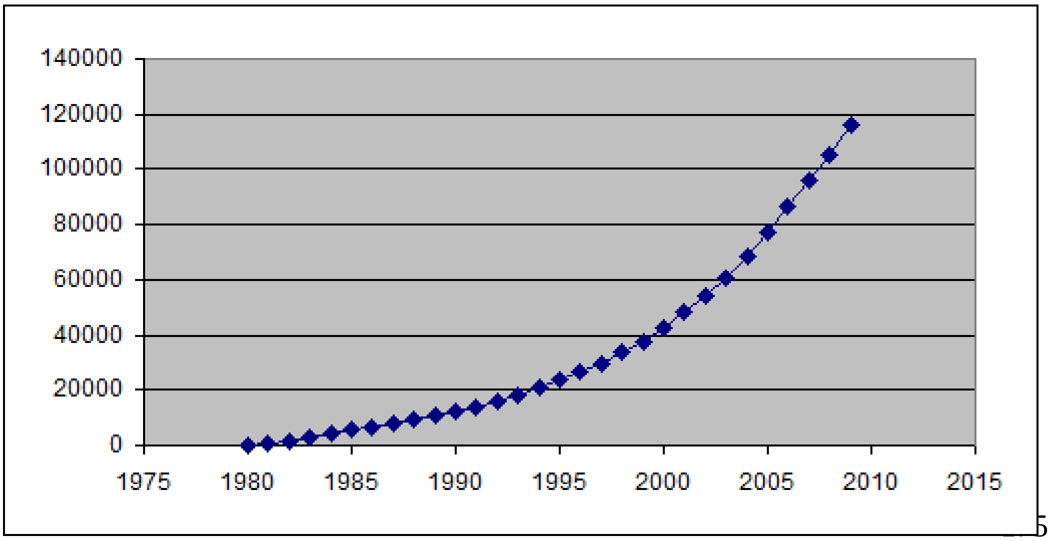
Year	Actual	Cum
2003	152	152
2004	1158	1310
2005	4111	5421
2006	5568	10989
2007	7451	18440
2008	8419	26859
2009	8588	35447



Appendix 2. Analogous products sales data

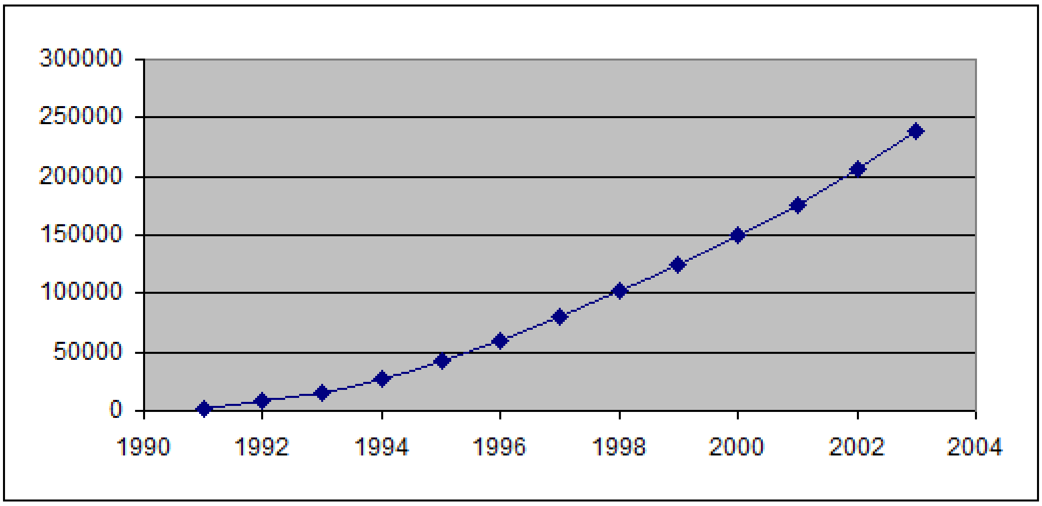
Aftermarket PC Monitors

Year	Actual	Cum
1980	197	197
1981	393	590
1982	609	1199
1983	1474	2673
1984	1563	4236
1985	1258	5494
1986	1160	6654
1987	1229	7883
1988	1376	9259
1989	1533	10792
1990	1573	12365
1991	1533	13898
1992	1917	15815
1993	2300	18115
1994	2470	20585
1995	2950	23535
1996	3050	26585
1997	3350	29935
1998	3710	33645
1999	4240	37885
2000	4740	42625
2001	5415	48040
2002	6186	54226
2003	6750	60976
2004	7825	68801
2005	8575	77376
2006	8956	86332
2007	9467	95799
2008	9656	105455
2009	10374	115829



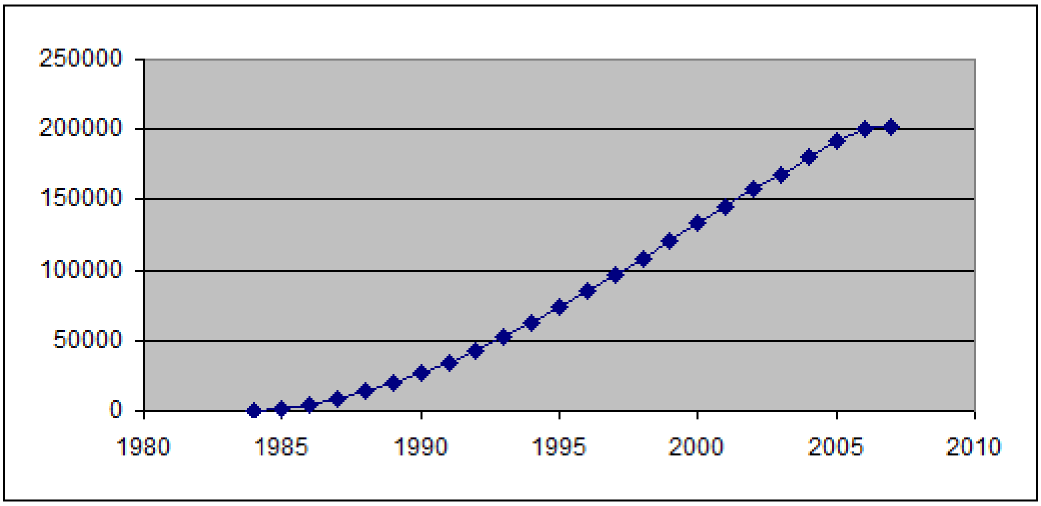
Aftermarket Remote Controls

Year	Actual	Cum
1991	2400	2400
1992	5500	7900
1993	7500	15400
1994	12600	28000
1995	15100	43100
1996	15871	58971
1997	20522	79493
1998	22886	102379
1999	22610	124989
2000	25474	150463
2001	24923	175386
2002	30738	206124
2003	33200	239324



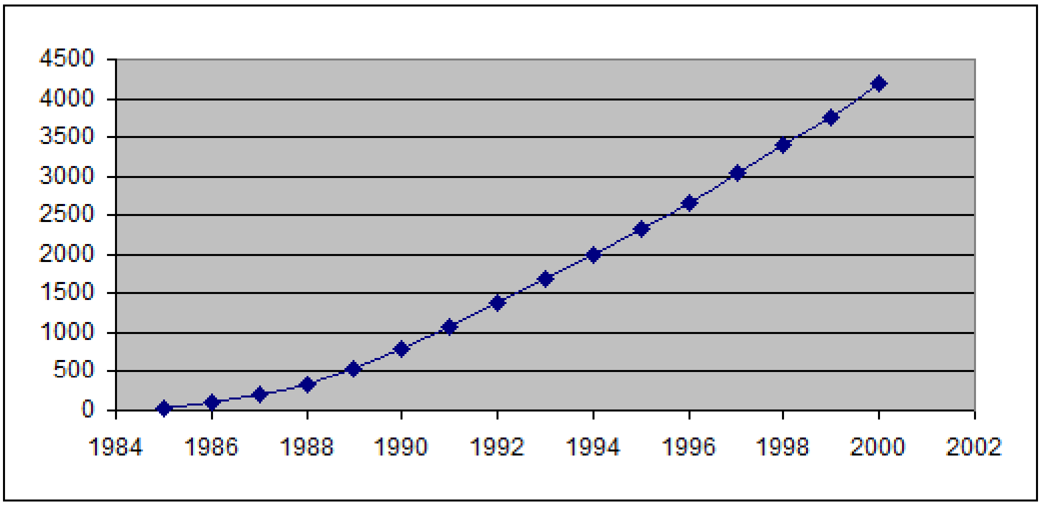
Analog Color TV with stereo

Year	Actual	Cum
1984	240	240
1985	1500	1740
1986	3116	4856
1987	4349	9205
1988	5090	14295
1989	6043	20338
1990	6655	26993
1991	7377	34370
1992	8534	42904
1993	9767	52671
1994	10438	63109
1995	10579	73688
1996	11189	84877
1997	11096	95973
1998	11955	107928
1999	12473	120401
2000	12799	133200
2001	11634	144834
2002	12233	157067
2003	10778	167845
2004	12304	180149
2005	12099	192248
2006	8615	200863
2007	1139	202002



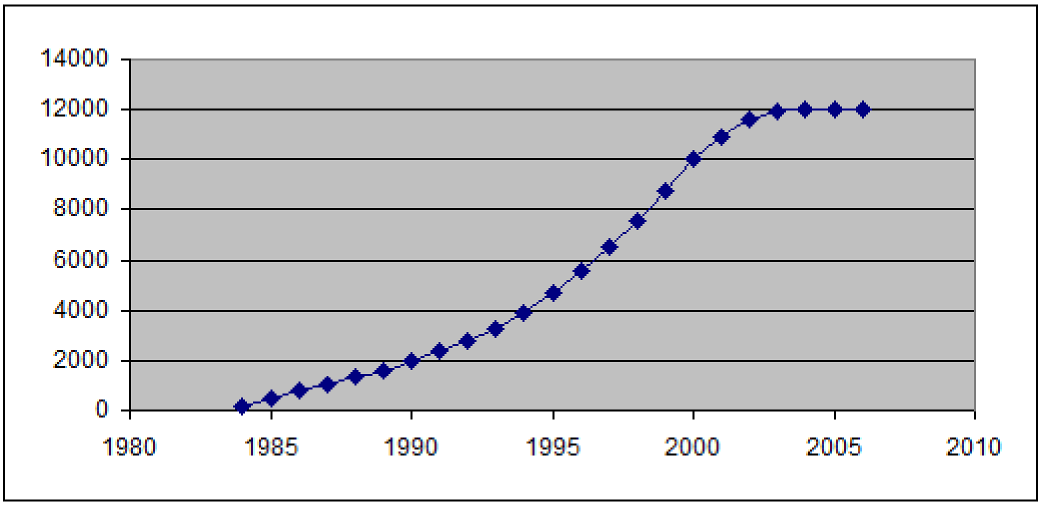
Analog Handheld LCD Color TV

Year	Actual	Cum
1985	25	25
1986	70	95
1987	100	195
1988	150	345
1989	200	545
1990	250	795
1991	280	1075
1992	300	1375
1993	300	1675
1994	310	1985
1995	335	2320
1996	350	2670
1997	360	3030
1998	366	3396
1999	367	3763
2000	425	4188
2001	445	4633



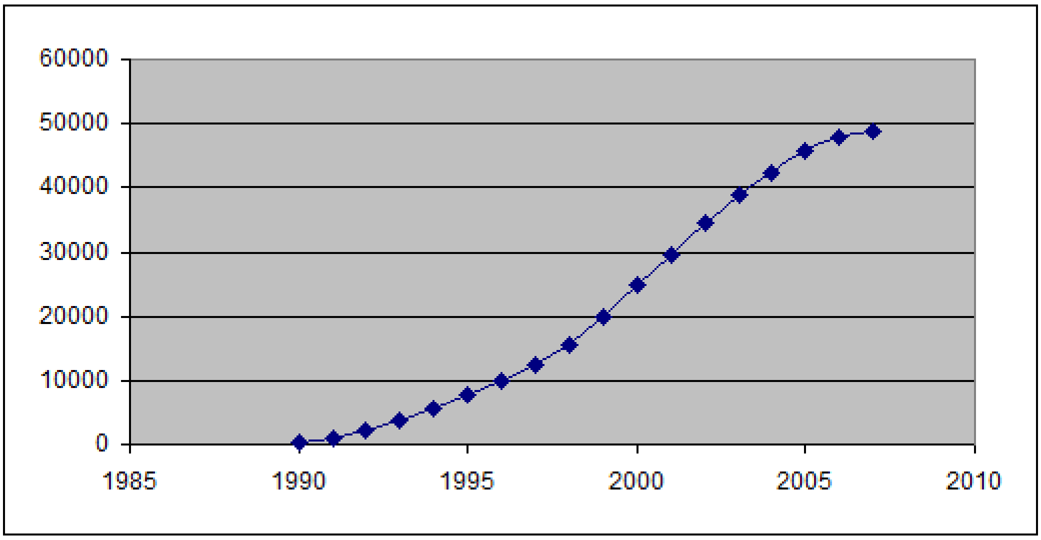
Analog Projection TV

Year	Actual	Cum
1984	195	195
1985	266	461
1986	304	765
1987	293	1058
1988	302	1360
1989	265	1625
1990	351	1976
1991	380	2356
1992	404	2760
1993	465	3225
1994	636	3861
1995	820	4681
1996	887	5568
1997	917	6485
1998	1070	7555
1999	1232	8787
2000	1216	10003
2001	933	10936
2002	681	11617
2003	276	11893
2004	97	11990
2005	20	12010
2006	5	12015



Analog TV/VCR Combinations

Year	Actual	Cum
1990	424	424
1991	662	1086
1992	936	2022
1993	1629	3651
1994	2017	5668
1995	2205	7873
1996	2199	10072
1997	2311	12383
1998	3147	15530
1999	4418	19948
2000	4964	24912
2001	4630	29542
2002	4870	34412
2003	4373	38785
2004	3643	42428
2005	3348	45776
2006	2022	47798
2007	875	48673

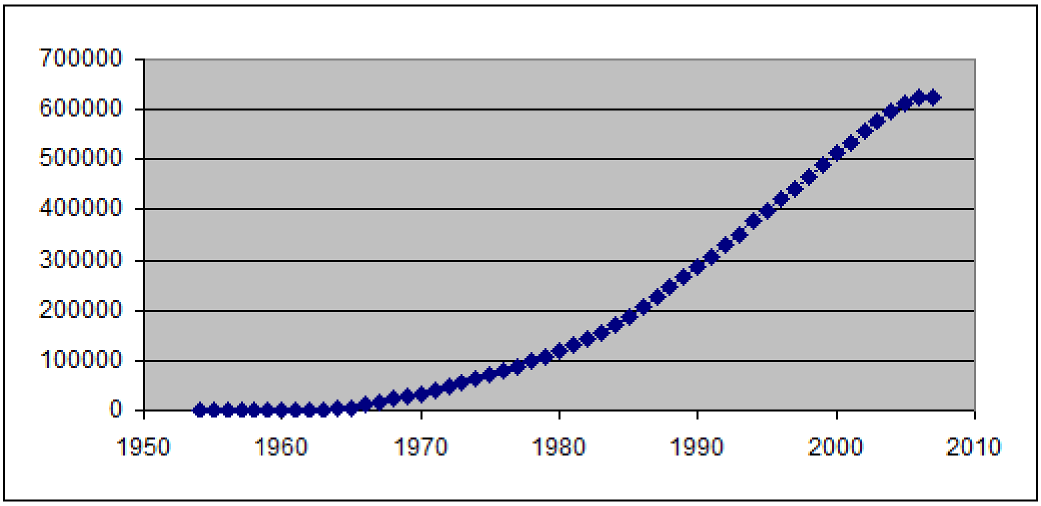


Analog TV

Year	Actual	Cum
1954	5	5
1955	20	25
1956	100	125
1957	85	210
1958	80	290
1959	90	380
1960	120	500
1961	147	647
1962	438	1085
1963	747	1832
1964	1404	3236
1965	2694	5930
1966	5012	10942
1967	5563	16505
1968	6215	22720
1969	6191	28911
1970	4821	33732
1971	6180	39912
1972	7555	47467
1973	9264	56731
1974	7830	64561
1975	6485	71046
1976	7700	78746
1977	9107	87853
1978	10236	98089
1979	9846	107935
1980	10897	118832
1981	11157	129989
1982	11366	141355
1983	13986	155341
1984	16083	171424
1985	16829	188253
1986	18204	206457
1987	19330	225787
1988	20216	246003
1989	21706	267709
1990	20384	288093
1991	19474	307567
1992	21056	328623
1993	23005	351628
1994	24715	376343
1995	23231	399574
1996	22384	421958
1997	21293	443251
1998	22204	465455
1999	23218	488673
2000	24175	512848
2001	21167	534015
2002	22469	556484

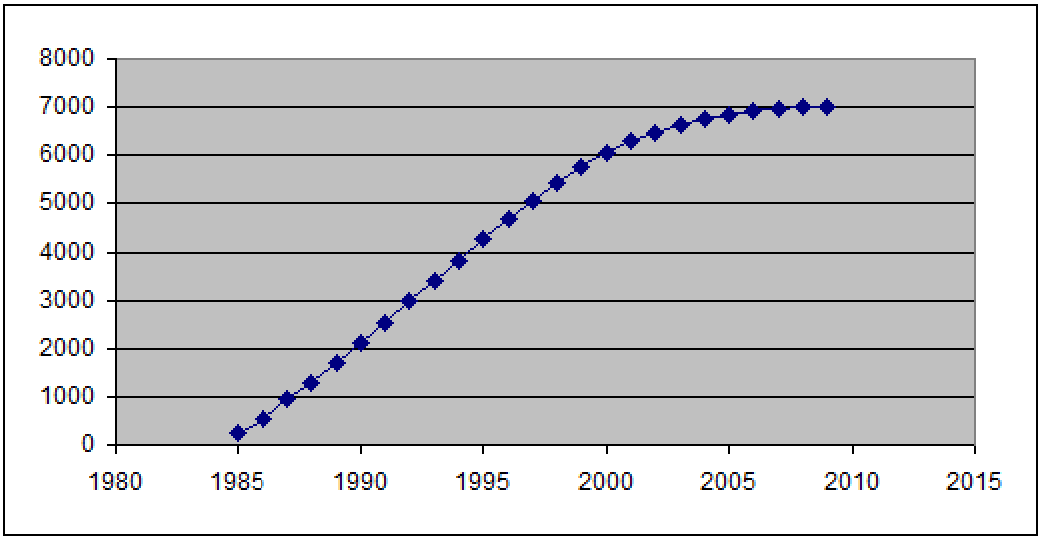
2003	20791	577275
2004	19934	597209
2005	16934	614143
2006	8761	622904
2007	1166	624070

Analog TV



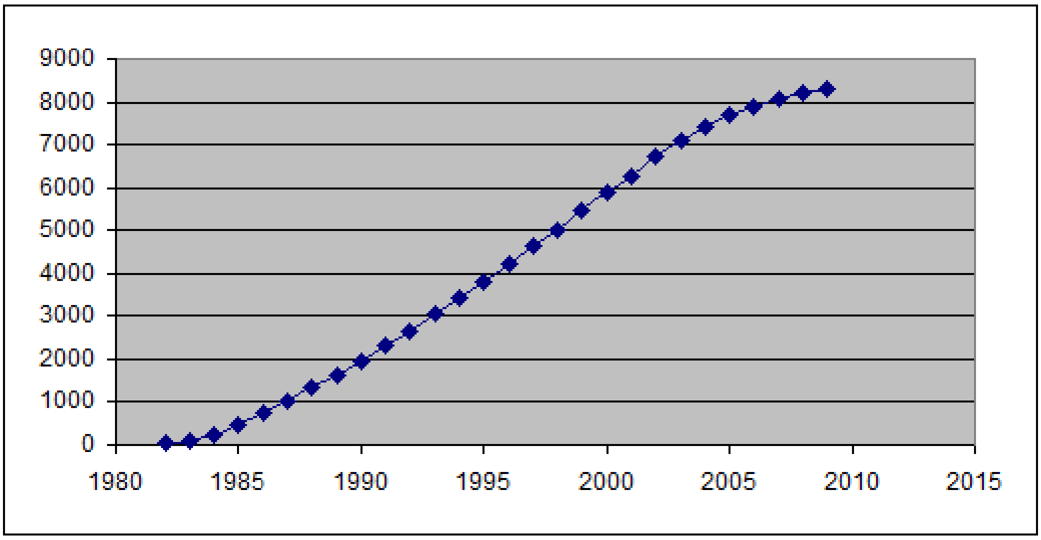
Blank audio cassettes

Year	Actual	Cum
1985	245	245
1986	296	541
1987	392	933
1988	366	1299
1989	390	1689
1990	428	2117
1991	421	2538
1992	426	2964
1993	427	3391
1994	437	3828
1995	438	4266
1996	423	4689
1997	376	5065
1998	355	5420
1999	335	5755
2000	294	6049
2001	246	6295
2002	186	6481
2003	149	6630
2004	128	6758
2005	96	6854
2006	65	6919
2007	50	6969
2008	33	7002
2009	22	7024



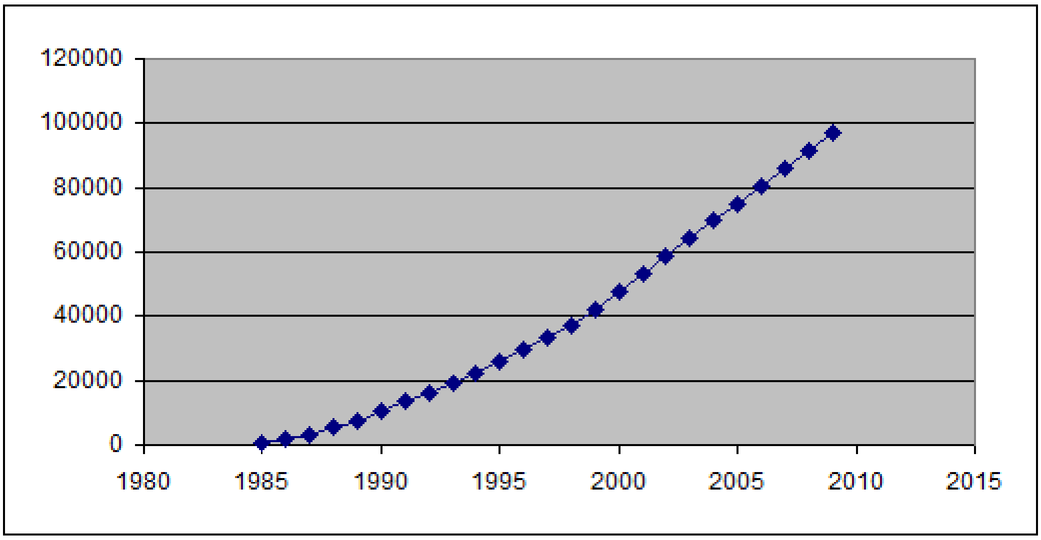
Blank video cassettes

Year	Actual	Cum
1982	25	25
1983	65	90
1984	133	223
1985	233	456
1986	296	752
1987	274	1026
1988	297	1323
1989	286	1609
1990	338	1947
1991	362	2309
1992	358	2667
1993	377	3044
1994	383	3427
1995	384	3811
1996	408	4219
1997	398	4617
1998	405	5022
1999	431	5453
2000	431	5884
2001	366	6250
2002	468	6718
2003	394	7112
2004	325	7437
2005	263	7700
2006	201	7901
2007	176	8077
2008	144	8221
2009	84	8305



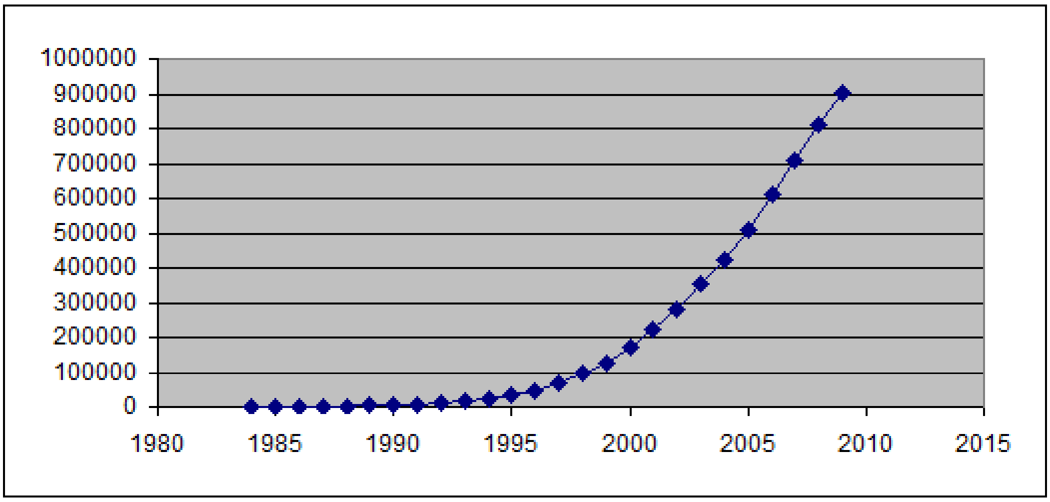
Camcorders

Year	Actual	Cum
1985	517	517
1986	1169	1686
1987	1604	3290
1988	2044	5334
1989	2286	7620
1990	2962	10582
1991	2864	13446
1992	2815	16261
1993	3088	19349
1994	3209	22558
1995	3560	26118
1996	3634	29752
1997	3650	33402
1998	3829	37231
1999	4790	42021
2000	5848	47869
2001	5284	53153
2002	5790	58943
2003	5262	64205
2004	5559	69764
2005	5242	75006
2006	5320	80326
2007	5558	85884
2008	5608	91492
2009	5853	97345



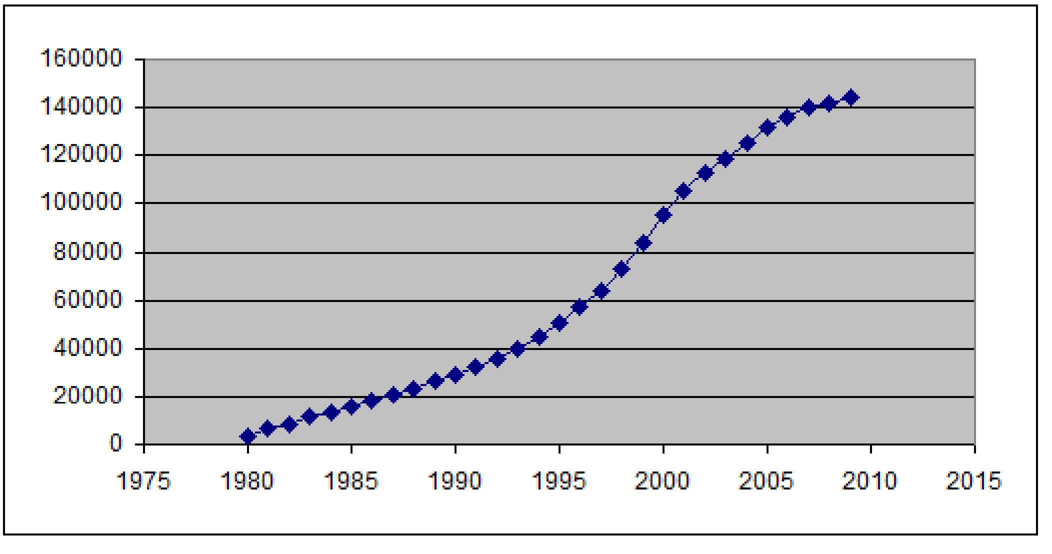
Cellular phones

Year	Actual	Cum
1984	23	23
1985	68	91
1986	259	350
1987	514	865
1988	810	1674
1989	1365	3039
1990	1665	4705
1991	2175	6880
1992	3481	10360
1993	5087	15447
1994	8031	23478
1995	9368	32846
1996	10524	43371
1997	24570	67941
1998	27300	95241
1999	30667	125908
2000	47866	173774
2001	48594	222368
2002	59141	281509
2003	69945	351454
2004	72690	424144
2005	86042	510186
2006	99472	609658
2007	101500	711158
2008	102800	813958
2009	86800	900758



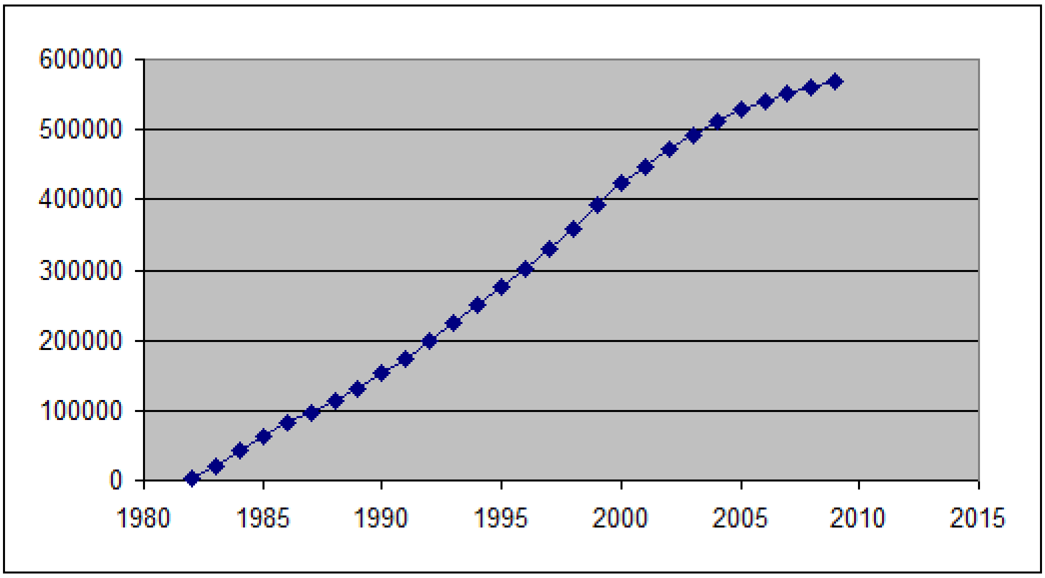
Compact audio system

Year	Actual	Cum
1980	3567	3567
1981	2720	6287
1982	2321	8608
1983	2651	11259
1984	1659	12918
1985	2531	15449
1986	2690	18139
1987	2315	20454
1988	3049	23503
1989	2878	26381
1990	2447	28828
1991	3139	31967
1992	3877	35844
1993	4100	39944
1994	5139	45083
1995	5677	50760
1996	6174	56934
1997	7275	64209
1998	8946	73155
1999	10600	83755
2000	11455	95210
2001	10028	105238
2002	7314	112552
2003	6118	118670
2004	6874	125544
2005	6010	131554
2006	4548	136102
2007	3592	139694
2008	2239	141933
2009	2330	144263



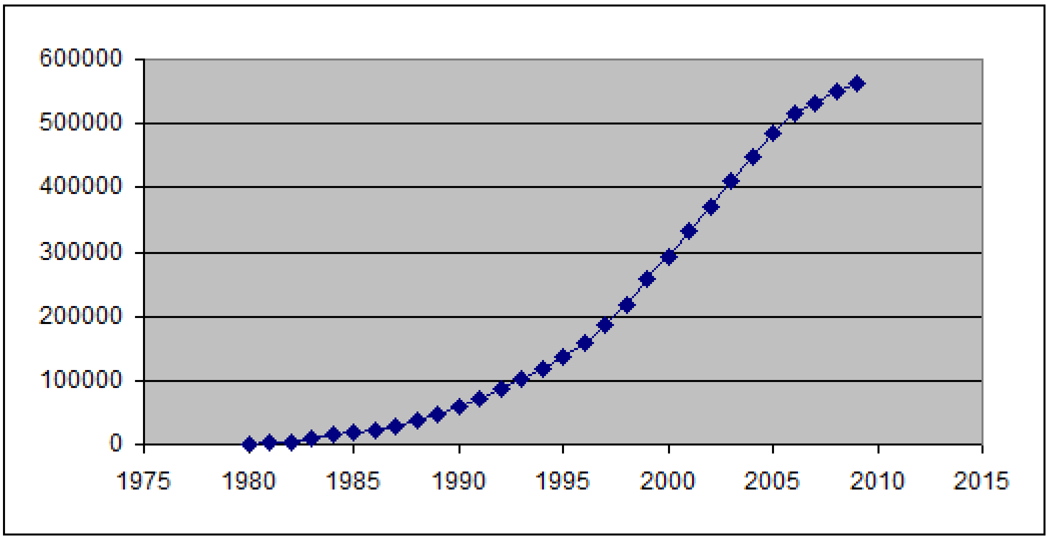
Corded telephones

Year	Actual	Cum
1982	3700	3700
1983	15000	18700
1984	24000	42700
1985	21000	63700
1986	18100	81800
1987	15900	97700
1988	15200	112900
1989	19000	131900
1990	22003	153903
1991	20872	174775
1992	23964	198739
1993	27080	225819
1994	23664	249483
1995	25836	275319
1996	26013	301332
1997	27805	329137
1998	28998	358135
1999	34486	392621
2000	29670	422291
2001	24957	447248
2002	23813	471061
2003	22102	493163
2004	17372	510535
2005	18466	529001
2006	12039	541040
2007	9227	550267
2008	9598	559865
2009	8913	568778



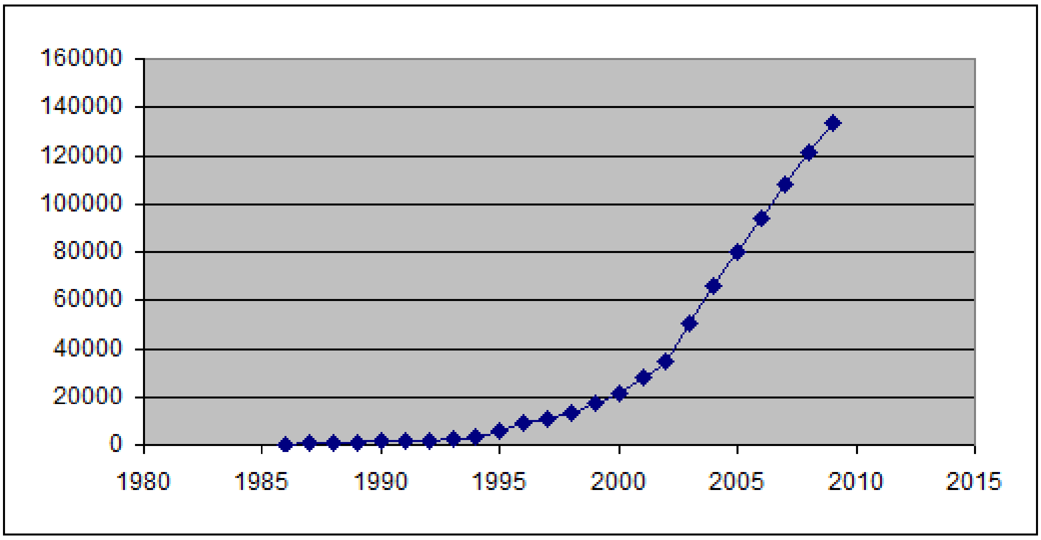
Cordless telephones

Year	Actual	Cum
1980	500	500
1981	1150	1650
1982	2200	3850
1983	4700	8550
1984	6300	14850
1985	4000	18850
1986	4100	22950
1987	6400	29350
1988	8200	37550
1989	10000	47550
1990	10148	57698
1991	13232	70930
1992	14944	85874
1993	16183	102057
1994	16772	118829
1995	19510	138339
1996	20555	158894
1997	28156	187050
1998	31261	218311
1999	39654	257965
2000	35090	293055
2001	40000	333055
2002	36556	369611
2003	40320	409931
2004	37605	447536
2005	36955	484491
2006	30571	515062
2007	17876	532938
2008	16602	549540
2009	14218	563758



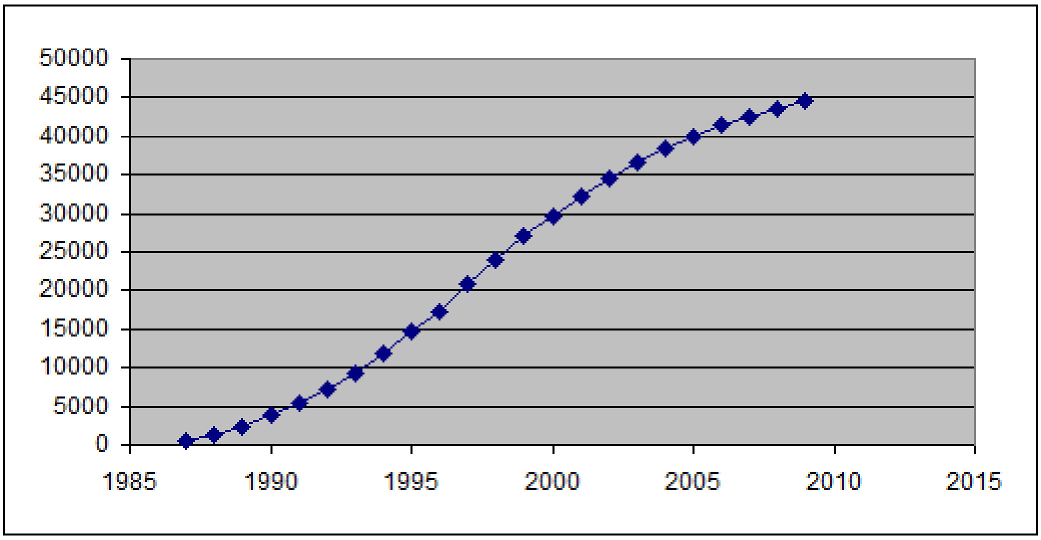
DBS Satellite

Year	Actual	Cum
1986	235	235
1987	250	485
1988	275	760
1989	300	1060
1990	330	1390
1991	281	1671
1992	303	1974
1993	349	2323
1994	1320	3643
1995	2235	5878
1996	2800	8678
1997	2200	10878
1998	2685	13563
1999	3625	17188
2000	4250	21438
2001	6431	27869
2002	6906	34775
2003	15170	49945
2004	16250	66195
2005	13939	80134
2006	13888	94022
2007	14025	108047
2008	13170	121217
2009	12690	133907



Fax machines

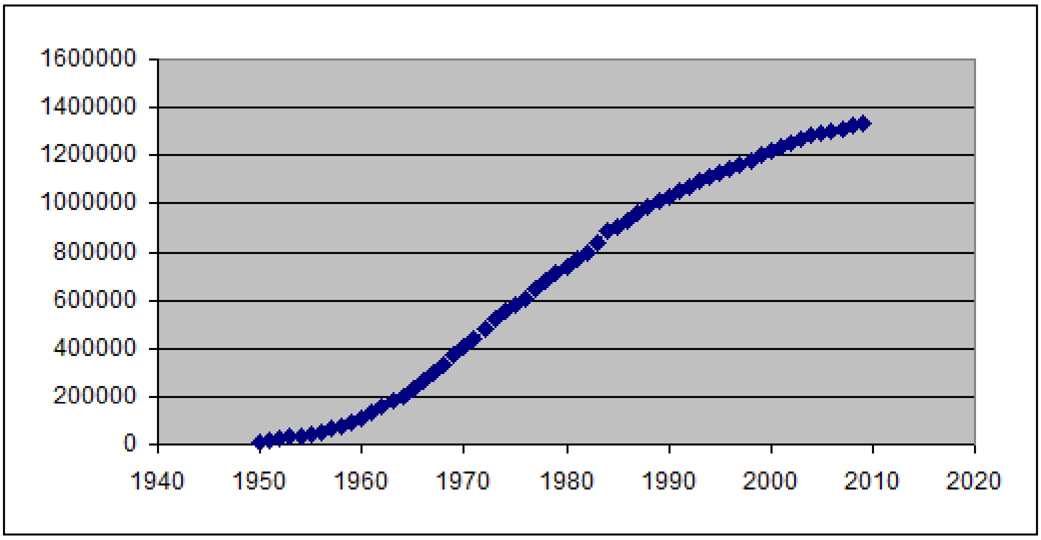
Year	Actual	Cum
1987	400	400
1988	800	1200
1989	1200	2400
1990	1483	3883
1991	1498	5381
1992	1731	7112
1993	2100	9212
1994	2536	11748
1995	2827	14575
1996	2761	17336
1997	3626	20962
1998	3048	24010
1999	3010	27020
2000	2700	29720
2001	2565	32285
2002	2300	34585
2003	2070	36655
2004	1790	38445
2005	1534	39979
2006	1400	41379
2007	1200	42579
2008	1050	43629
2009	975	44604



Home radio

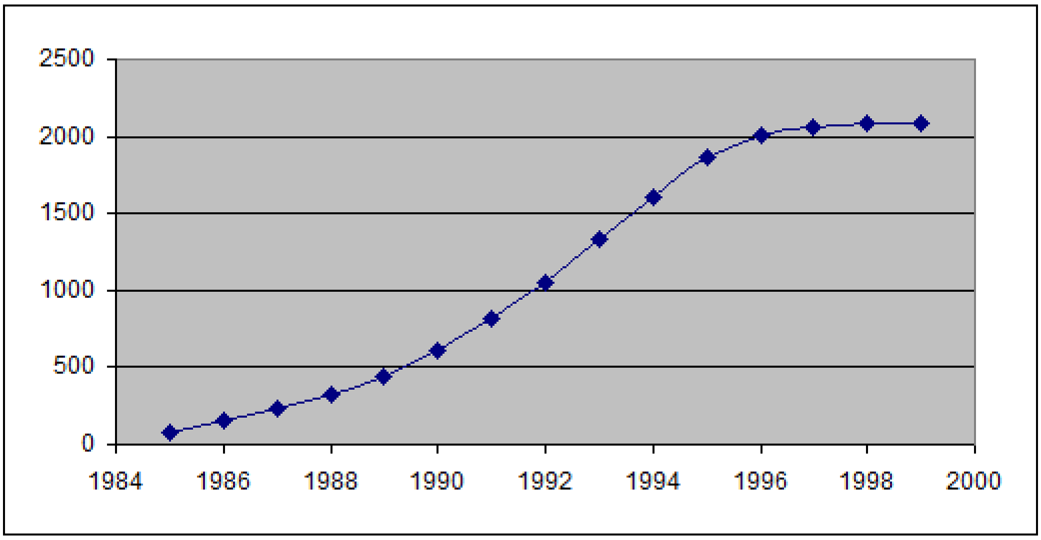
Year	Actual	Cum
1950	9218	9218
1951	6445	15663
1952	7232	22895
1953	7283	30178
1954	6119	36297
1955	7327	43624
1956	8951	52575
1957	9952	62527
1958	10797	73324
1959	15772	89096
1960	18031	107127
1961	23654	130781
1962	24781	155562
1963	23602	179164
1964	23558	202722
1965	31689	234411
1966	34779	269190
1967	31684	300874
1968	34332	335206
1969	39414	374620
1970	34049	408669
1971	34105	442774
1972	42149	484923
1973	36968	521891
1974	33076	554967
1975	25434	580401
1976	28198	608599
1977	41430	650029
1978	31760	681789
1979	27684	709473
1980	28062	737535
1981	29415	766950
1982	32663	799613
1983	39496	839109
1984	46456	885565
1985	21575	907140
1986	25364	932504
1987	28110	960614
1988	23623	984237
1989	25254	1009491
1990	21585	1031076
1991	18530	1049606
1992	21553	1071159
1993	19697	1090856
1994	18325	1109181
1995	17051	1126232
1996	17581	1143813
1997	17664	1161477
1998	18734	1180211

1999	19899	1200110
2000	19976	1220086
2001	18200	1238286
2002	16194	1254480
2003	16535	1271015
2004	9983	1280998
2005	9066	1290064
2006	9059	1299123
2007	13320	1312443
2008	12795	1325238
2009	12180	1337418



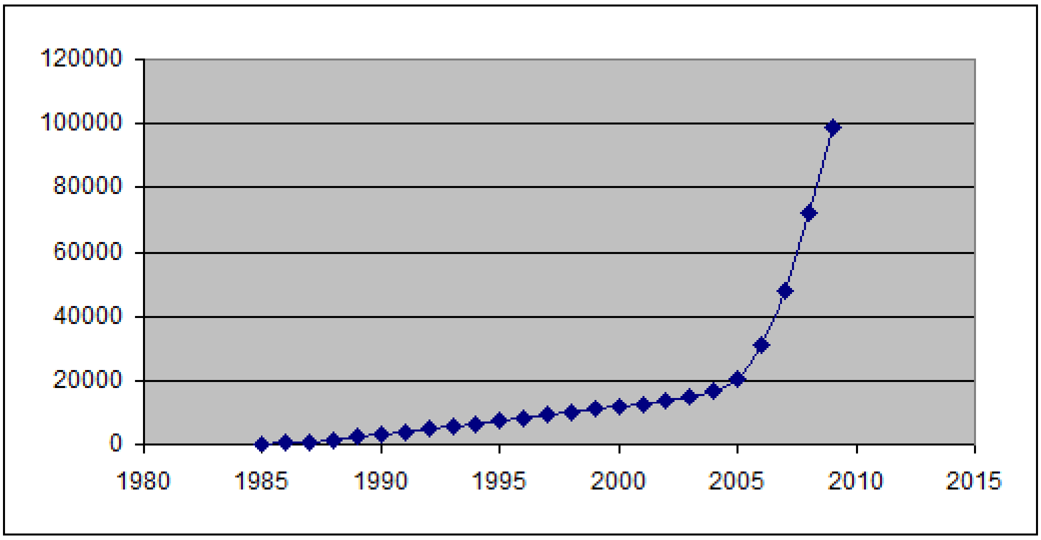
Laserdisc Player

Year	Actual	Cum
1985	75	75
1986	85	160
1987	75	235
1988	90	325
1989	120	445
1990	168	613
1991	206	819
1992	224	1043
1993	287	1330
1994	272	1602
1995	257	1859
1996	155	2014
1997	49	2063
1998	20	2083
1999	7	2090



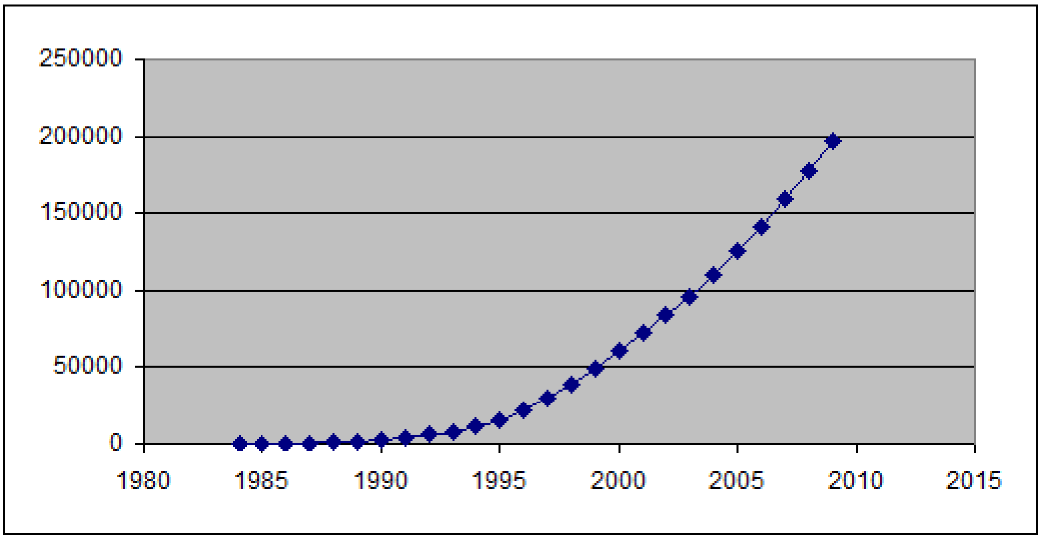
LCD TV

Year	Actual	Cum
1985	150	150
1986	245	395
1987	350	745
1988	675	1420
1989	850	2270
1990	875	3145
1991	880	4025
1992	825	4850
1993	800	5650
1994	835	6485
1995	885	7370
1996	900	8270
1997	895	9165
1998	901	10066
1999	867	10933
2000	832	11765
2001	845	12610
2002	935	13545
2003	1253	14798
2004	1842	16640
2005	4077	20717
2006	10325	31042
2007	16843	47885
2008	24116	72001
2009	26790	98791



Fax modem

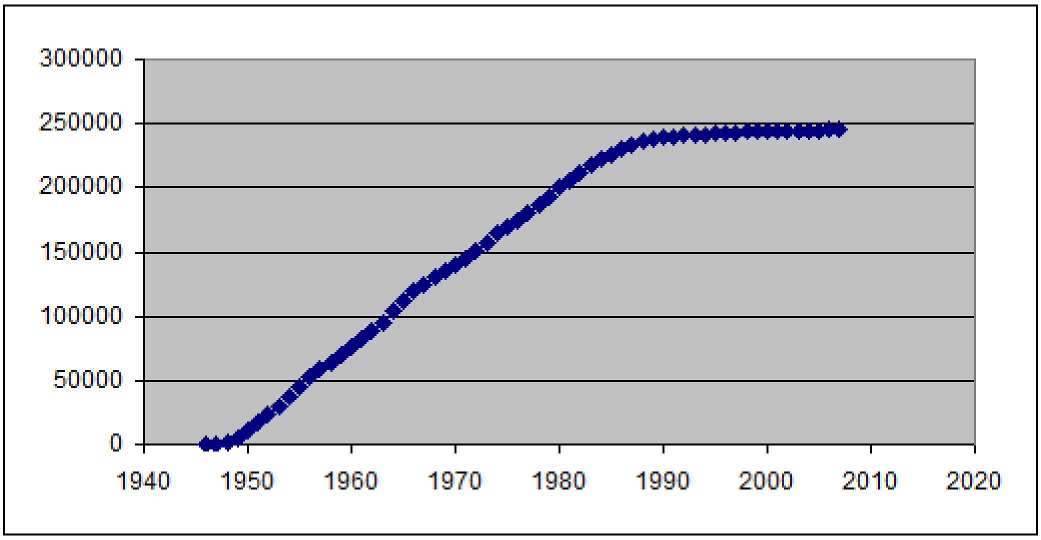
Year	Actual	Cum
1984	13	13
1985	39	52
1986	148	200
1987	294	494
1988	463	957
1989	780	1737
1990	952	2689
1991	1243	3932
1992	1990	5922
1993	2220	8142
1994	2900	11042
1995	4670	15712
1996	6350	22062
1997	7800	29862
1998	9000	38862
1999	10500	49362
2000	11500	60862
2001	11500	72362
2002	11750	84112
2003	12337	96449
2004	13765	110214
2005	15450	125664
2006	16150	141814
2007	17604	159418
2008	18467	177885
2009	19408	197293



Monochrome TV

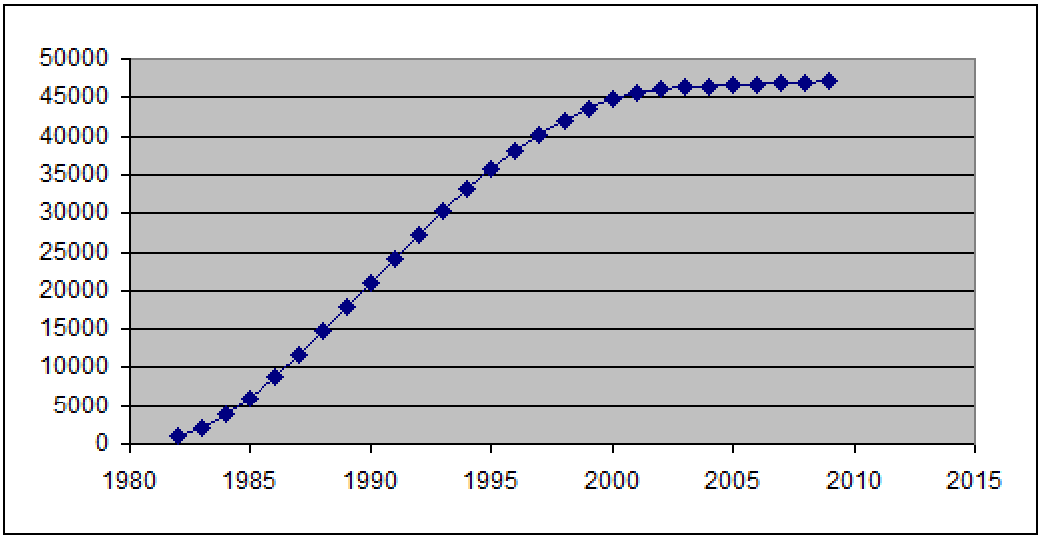
Year	Actual	Cum
1946	6	6
1947	179	185
1948	970	1155
1949	2970	4125
1950	7355	11480
1951	5312	16792
1952	6194	22986
1953	6870	29856
1954	7405	37261
1955	7738	44999
1956	7351	52350
1957	6388	58738
1958	5051	63789
1959	6278	70067
1960	5707	75774
1961	6155	81929
1962	6558	88487
1963	7019	95506
1964	8028	103534
1965	8409	111943
1966	7189	119132
1967	5290	124422
1968	5778	130200
1969	5191	135391
1970	4704	140095
1971	4841	144936
1972	5512	150448
1973	7242	157690
1974	6318	164008
1975	4955	168963
1976	5561	174524
1977	5952	180476
1978	6461	186937
1979	6529	193466
1980	6684	200150
1981	5654	205804
1982	5692	211496
1983	5735	217231
1984	5050	222281
1985	3684	225965
1986	3953	229918
1987	3547	233465
1988	2574	236039
1989	1656	237695
1990	1411	239106
1991	784	239890
1992	633	240523
1993	550	241073
1994	540	241613

1995	480	242093
1996	425	242518
1997	400	242918
1998	347	243265
1999	320	243585
2000	265	243850
2001	250	244100
2002	225	244325
2003	200	244525
2004	150	244675
2005	125	244800
2006	110	244910
2007	50	244960



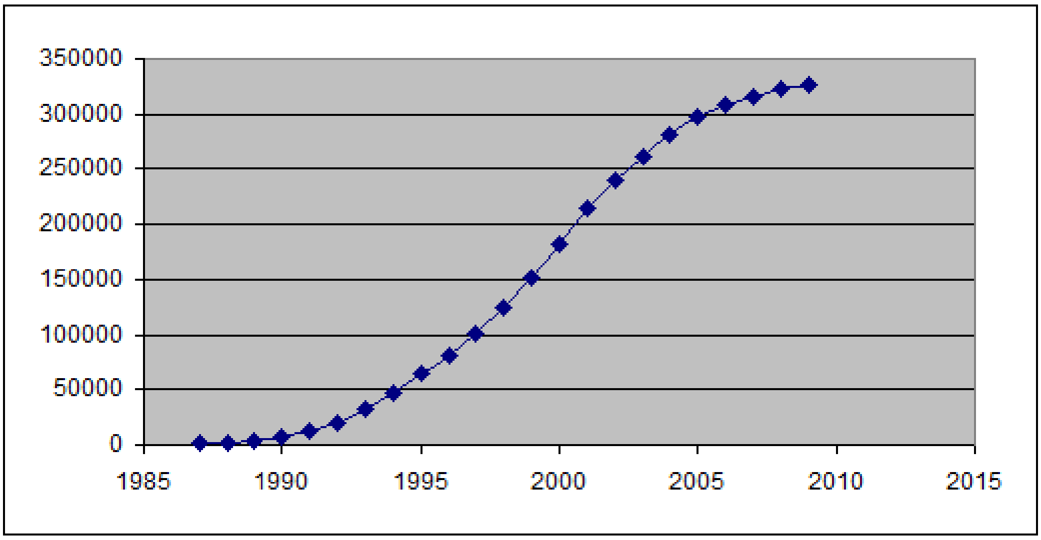
Personal wordprocessor

Year	Actual	Cum
1982	1000	1000
1983	1200	2200
1984	1800	4000
1985	2000	6000
1986	2700	8700
1987	2900	11600
1988	3100	14700
1989	3200	17900
1990	3200	21100
1991	3000	24100
1992	3000	27100
1993	3100	30200
1994	2880	33080
1995	2650	35730
1996	2450	38180
1997	2100	40280
1998	1750	42030
1999	1550	43580
2000	1240	44820
2001	868	45688
2002	434	46122
2003	215	46337
2004	142	46479
2005	136	46615
2006	133	46748
2007	127	46875
2008	117	46992
2009	115	47107



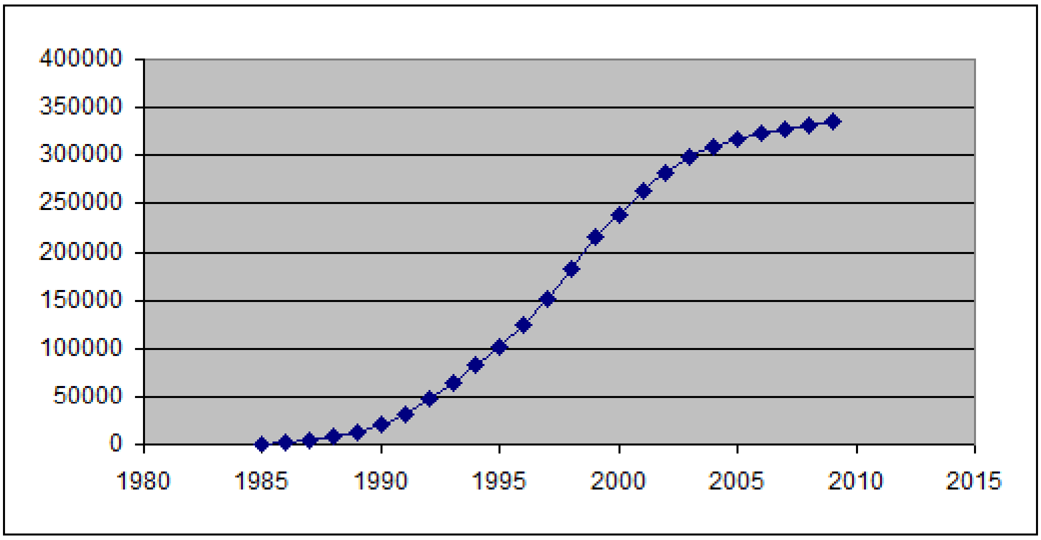
Portable TV equipment

Year	Actual	Cum
1987	903	903
1988	1541	2444
1989	1929	4373
1990	3186	7559
1991	4681	12240
1992	8341	20581
1993	11276	31857
1994	15262	47119
1995	17849	64968
1996	16970	81938
1997	18668	100606
1998	23726	124332
1999	26414	150746
2000	32161	182907
2001	31707	214614
2002	24481	239095
2003	23347	262442
2004	18929	281371
2005	17072	298443
2006	10810	309253
2007	7217	316470
2008	6240	322710
2009	4668	327378



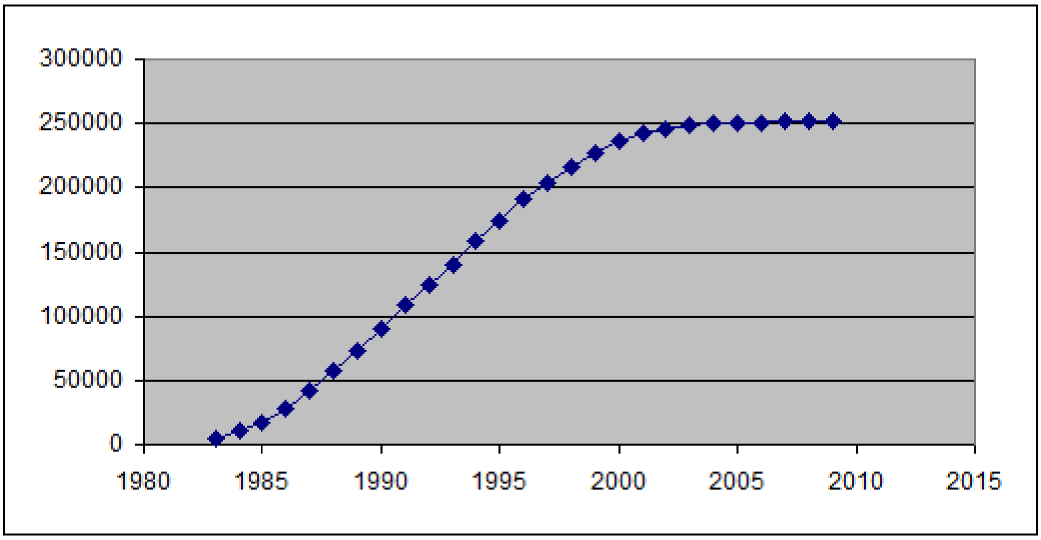
Portable Headset Audio

Year	Actual	Cum
1985	903	903
1986	1541	2444
1987	1929	4373
1988	3186	7559
1989	4681	12240
1990	8341	20581
1991	11276	31857
1992	15262	47119
1993	17849	64968
1994	16970	81938
1995	18668	100606
1996	23726	124332
1997	26414	150746
1998	32161	182907
1999	31707	214614
2000	24481	239095
2001	23347	262442
2002	18929	281371
2003	17072	298443
2004	10810	309253
2005	7217	316470
2006	6240	322710
2007	4668	327378
2008	4669	332047
2009	4670	336717



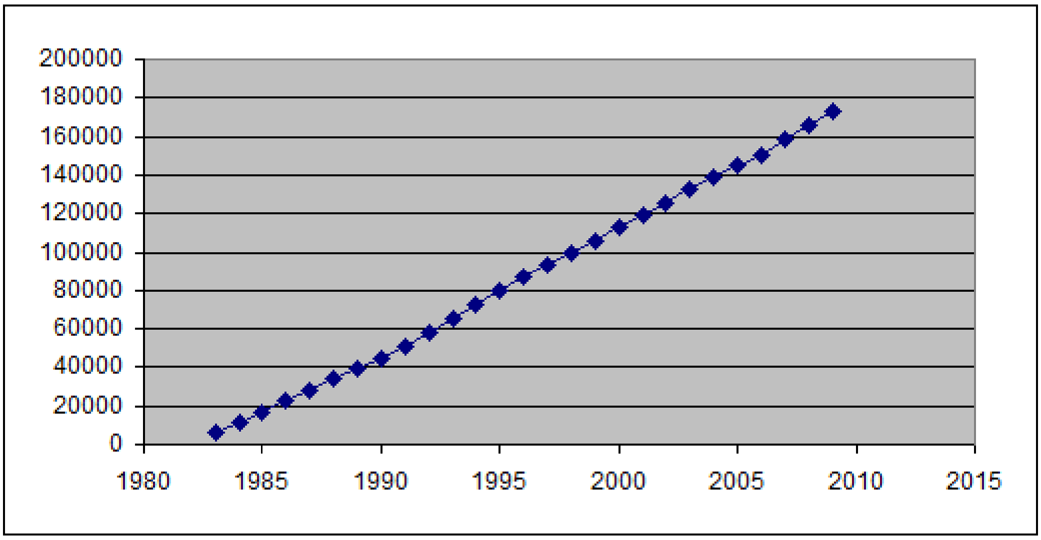
Portable Tape and Radio/Tape Players

Year	Actual	Cum
1983	4502	4502
1984	5614	10116
1985	7643	17759
1986	10374	28133
1987	13830	41963
1988	15010	56973
1989	16648	73621
1990	17117	90738
1991	17740	108478
1992	16319	124797
1993	15717	140514
1994	17988	158502
1995	16173	174675
1996	15959	190634
1997	13152	203786
1998	12505	216291
1999	10837	227128
2000	8952	236080
2001	6378	242458
2002	3313	245771
2003	2178	247949
2004	1646	249595
2005	690	250285
2006	578	250863
2007	480	251343
2008	377	251720
2009	301	252021



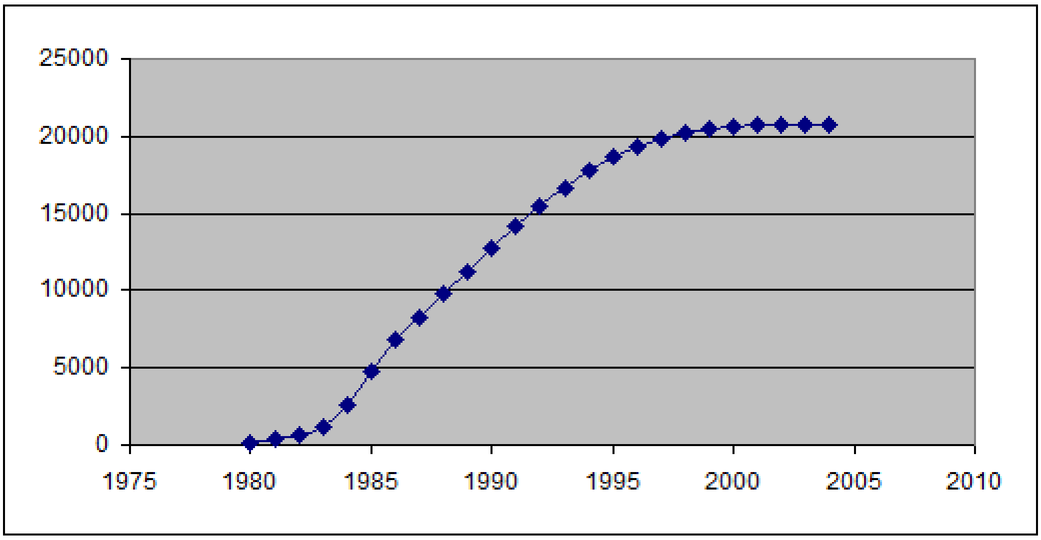
Portable tape recorder

Year	Actual	Cum
1983	6464	6464
1984	5349	11813
1985	5146	16959
1986	5447	22406
1987	5670	28076
1988	6156	34232
1989	5474	39706
1990	5341	45047
1991	5831	50878
1992	7004	57882
1993	7054	64936
1994	7451	72387
1995	7788	80175
1996	6803	86978
1997	6396	93374
1998	6529	99903
1999	6271	106174
2000	6501	112675
2001	6494	119169
2002	6667	125836
2003	6492	132328
2004	6875	139203
2005	5635	144838
2006	5650	150488
2007	7576	158064
2008	7684	165748
2009	7553	173301



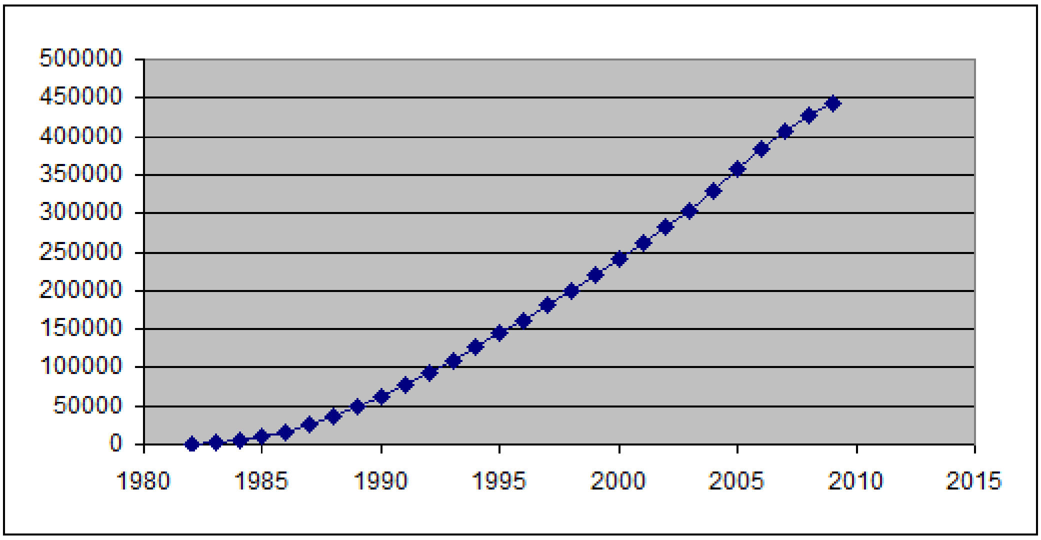
Rack audio system

Year	Actual	Cum
1980	178	178
1981	200	378
1982	319	697
1983	403	1100
1984	1540	2640
1985	2159	4799
1986	1979	6778
1987	1427	8205
1988	1527	9732
1989	1438	11170
1990	1557	12727
1991	1415	14142
1992	1341	15483
1993	1116	16599
1994	1143	17742
1995	944	18686
1996	695	19381
1997	501	19882
1998	367	20249
1999	270	20519
2000	151	20670
2001	79	20749
2002	31	20780
2003	19	20799
2004	8	20807



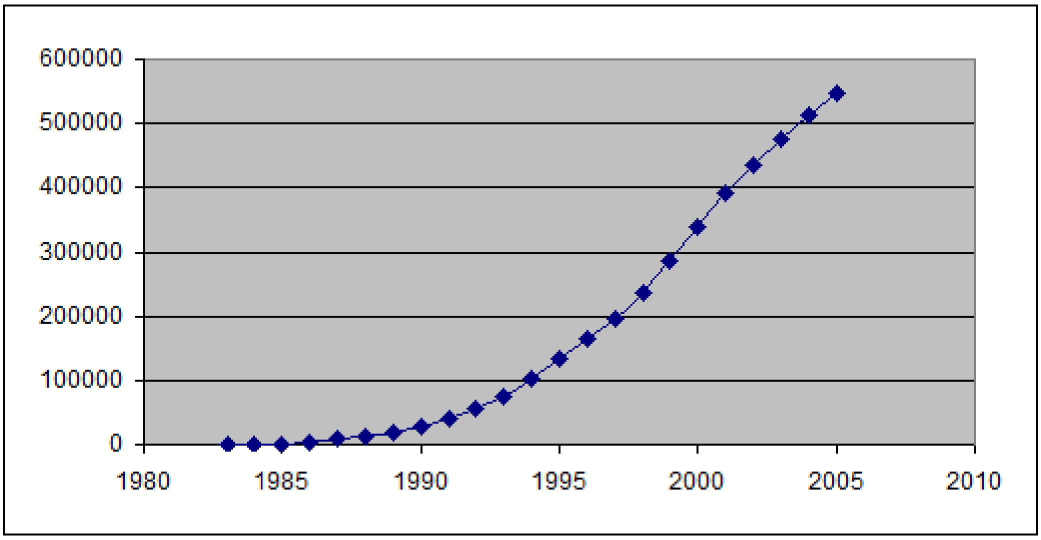
Telephone answering device

Year	Actual	Cum
1982	850	850
1983	2200	3050
1984	3000	6050
1985	4220	10270
1986	6450	16720
1987	8800	25520
1988	11100	36620
1989	12500	49120
1990	13560	62680
1991	15380	78060
1992	14590	92650
1993	16279	108929
1994	17613	126542
1995	17498	144040
1996	17570	161610
1997	18897	180507
1998	18519	199026
1999	20939	219965
2000	19876	239841
2001	21225	261066
2002	20737	281803
2003	22534	304337
2004	24083	328420
2005	27973	356393
2006	26202	382595
2007	24029	406624
2008	20175	426799
2009	15742	442541



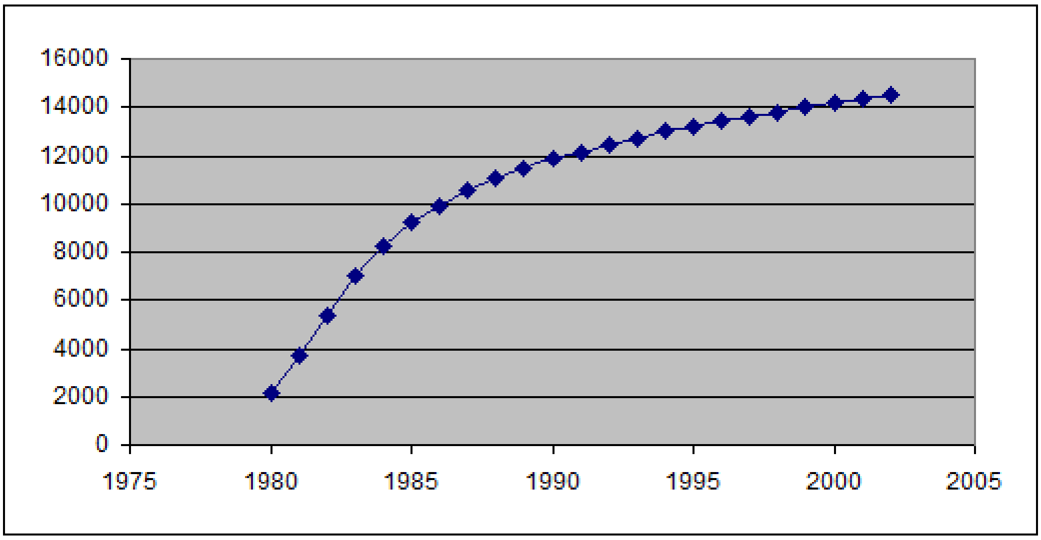
CD Players

Year	Actual	Cum
1983	35	35
1984	208	243
1985	1000	1243
1986	2600	3843
1987	4067	7910
1988	3973	11883
1989	6914	18797
1990	9155	27952
1991	11595	39547
1992	16134	55681
1993	20425	76106
1994	26913	103019
1995	30605	133624
1996	29708	163332
1997	33130	196462
1998	40874	237336
1999	47244	284580
2000	54776	339356
2001	52200	391556
2002	42914	434470
2003	40416	474886
2004	37475	512361
2005	33639	546000



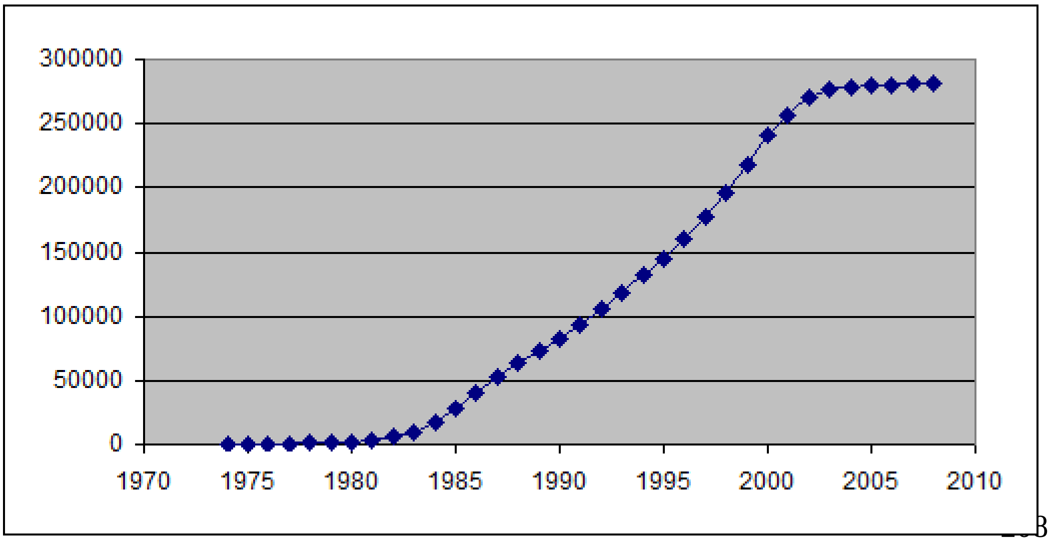
Turntables

Year	Actual	Cum
1980	2138	2138
1981	1600	3738
1982	1656	5394
1983	1646	7040
1984	1239	8279
1985	940	9219
1986	705	9924
1987	616	10540
1988	521	11061
1989	442	11503
1990	334	11837
1991	270	12107
1992	311	12418
1993	310	12728
1994	264	12992
1995	236	13228
1996	195	13423
1997	186	13609
1998	198	13807
1999	190	13997
2000	183	14180
2001	177	14357
2002	153	14510



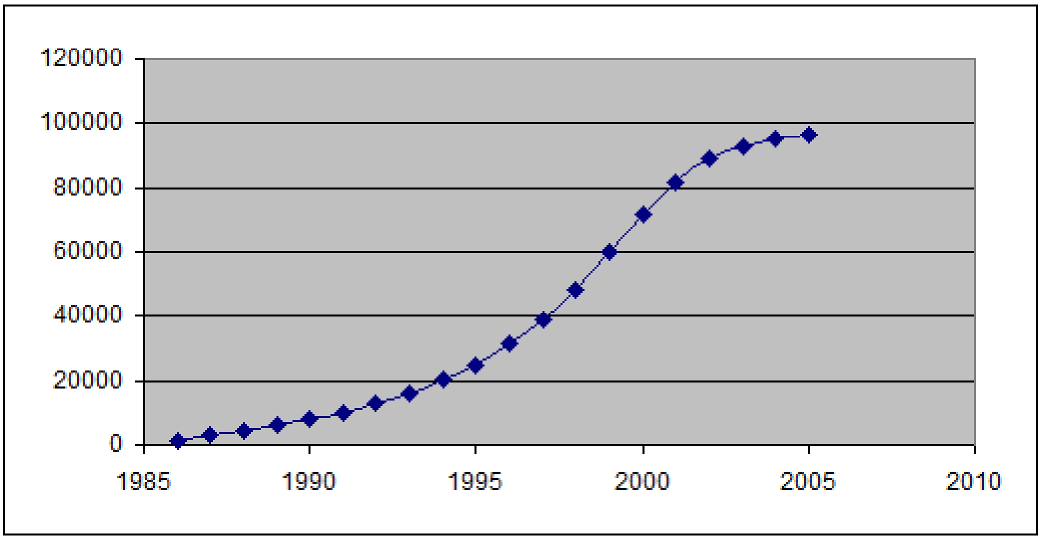
VCR Deck

Year	Actual	Cum
1974	34	34
1975	40	74
1976	70	144
1977	250	394
1978	402	796
1979	475	1271
1980	805	2076
1981	1361	3437
1982	2035	5472
1983	4091	9563
1984	7616	17179
1985	11336	28515
1986	12005	40520
1987	11702	52222
1988	10748	62970
1989	9760	72730
1990	10119	82849
1991	10718	93567
1992	12329	105896
1993	12448	118344
1994	13087	131431
1995	13562	144993
1996	15641	160634
1997	16673	177307
1998	18113	195420
1999	22809	218229
2000	23072	241301
2001	14910	256211
2002	13538	269749
2003	6416	276165
2004	2267	278432
2005	1365	279797
2006	759	280556
2007	53	280609
2008	6	280615



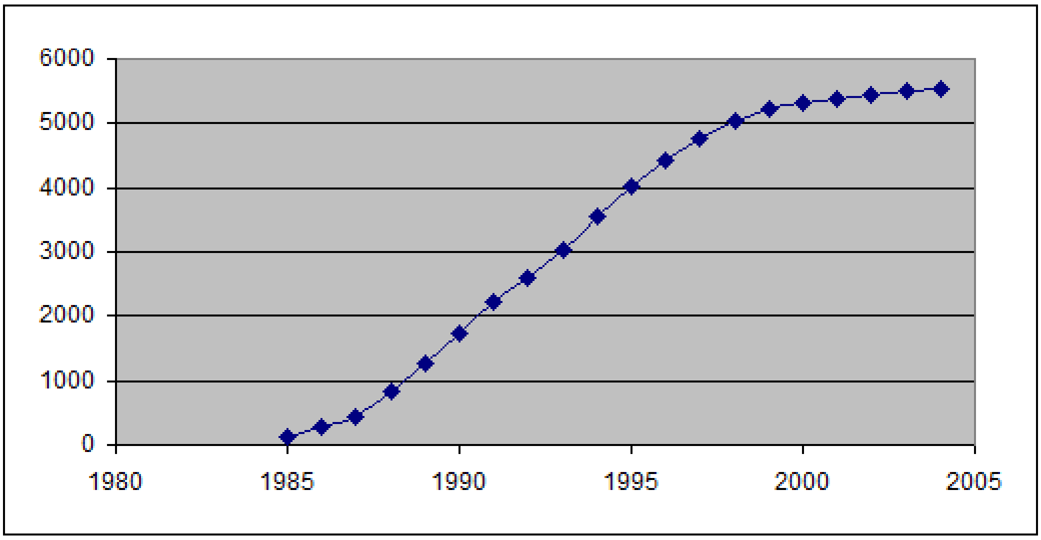
VCR deck with stereo

Year	Actual	Cum
1986	1200	1200
1987	2000	3200
1988	1400	4600
1989	1465	6065
1990	1867	7932
1991	2252	10184
1992	2941	13125
1993	3248	16373
1994	3777	20150
1995	4828	24978
1996	6675	31653
1997	7609	39262
1998	9085	48347
1999	11538	59885
2000	12045	71930
2001	9916	81846
2002	7149	88995
2003	3995	92990
2004	2267	95257
2005	1365	96622



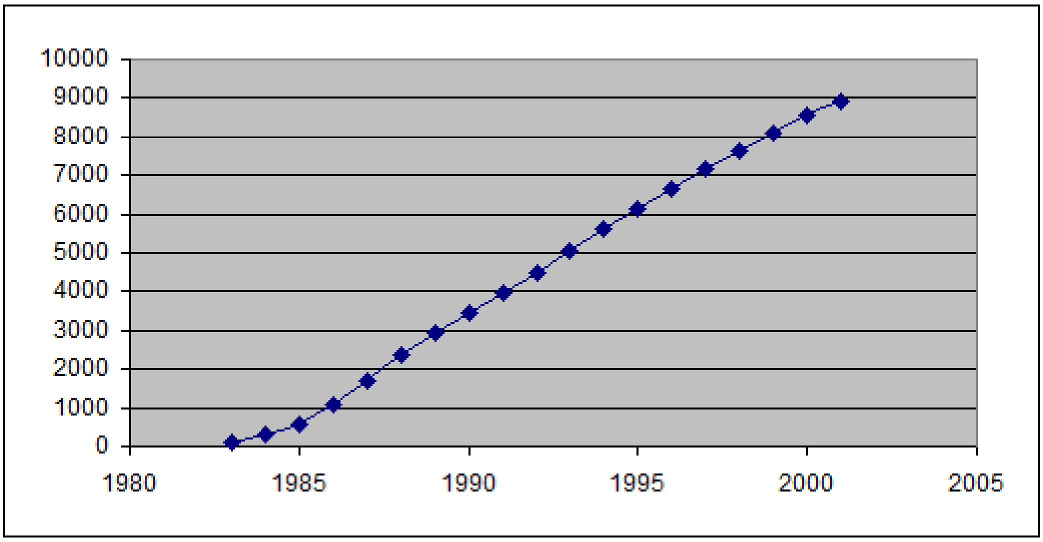
Videocassette Players

Year	Actual	Cum
1985	125	125
1986	150	275
1987	160	435
1988	395	830
1989	440	1270
1990	460	1730
1991	504	2234
1992	349	2583
1993	449	3032
1994	510	3542
1995	491	4033
1996	389	4422
1997	350	4772
1998	260	5032
1999	180	5212
2000	100	5312
2001	78	5390
2002	63	5453
2003	45	5498
2004	40	5538



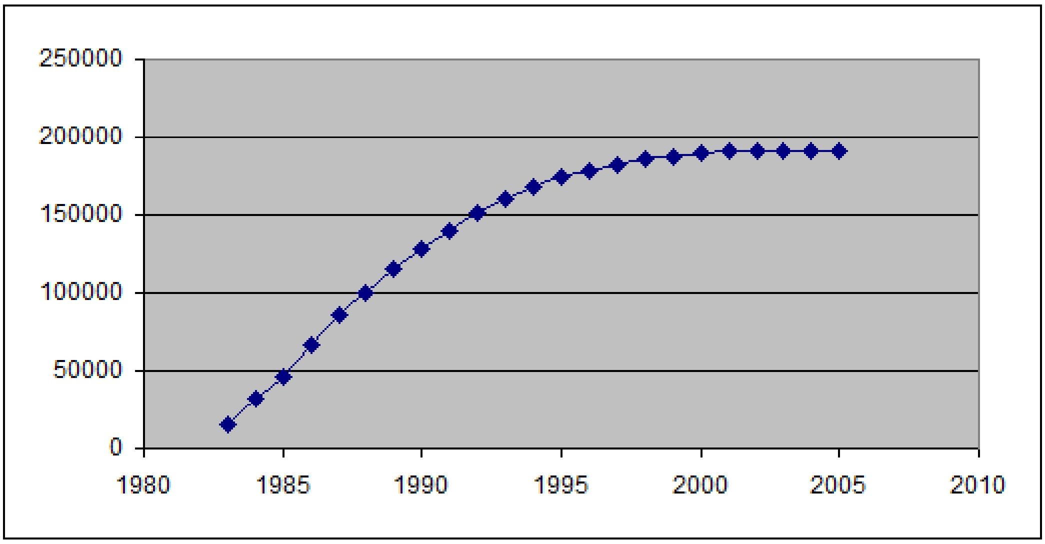
Analog Handheld LCD Monochrome TV

1983	125	125
1984	175	300
1985	250	550
1986	525	1075
1987	650	1725
1988	625	2350
1989	600	2950
1990	525	3475
1991	500	3975
1992	525	4500
1993	550	5050
1994	550	5600
1995	535	6135
1996	535	6670
1997	500	7170
1998	474	7644
1999	465	8109
2000	425	8534
2001	400	8934



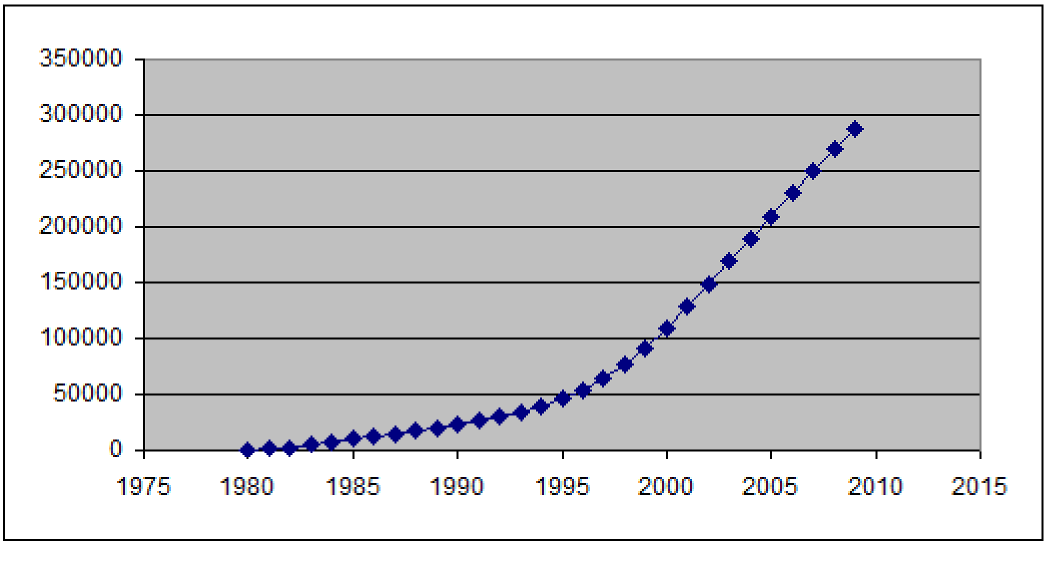
Boomboxes (Non-CD)

1983	14850	14850
1984	17298	32148
1985	14500	46648
1986	20461	67109
1987	18666	85775
1988	13728	99503
1989	15708	115211
1990	13510	128721
1991	11416	140137
1992	10581	150718
1993	9571	160289
1994	7771	168060
1995	6265	174325
1996	4420	178745
1997	3770	182515
1998	2760	185275
1999	2515	187790
2000	1803	189593
2001	831	190424
2002	446	190870
2003	329	191199
2004	347	191546
2005	51	191597



PC Printers

1980	369	369
1981	738	1107
1982	1145	2252
1983	2769	5021
1984	2935	7956
1985	2363	10319
1986	2178	12497
1987	2308	14805
1988	2585	17390
1989	2880	20270
1990	2954	23224
1991	2880	26104
1992	3600	29704
1993	4320	34024
1994	5160	39184
1995	6480	45664
1996	8400	54064
1997	10400	64464
1998	12500	76964
1999	15000	91964
2000	17400	109364
2001	18800	128164
2002	20300	148464
2003	21518	169982
2004	19581	189563
2005	19973	209536
2006	20273	229809
2007	21001	250810
2008	19170	269980
2009	18403	288383



Personal Computers

1980	500	500
1981	1000	1500
1982	1550	3050
1983	3750	6800
1984	3975	10775
1985	3200	13975
1986	2950	16925
1987	3125	20050
1988	3500	23550
1989	3900	27450
1990	4000	31450
1991	3900	35350
1992	4875	40225
1993	5850	46075
1994	6725	52800
1995	8400	61200
1996	9400	70600
1997	11000	81600
1998	12800	94400
1999	14900	109300
2000	16400	125700
2001	14400	140100
2002	15100	155200
2003	18120	173320
2004	20000	193320
2005	22400	215720
2006	24416	240136
2007	26000	266136
2008	27604	293740
2009	29000	322740